ERASMUS UNIVERSITY ROTTERDAM

VISUALS IN THE MUSIC INDUSTRY

Faculty : Erasmus School of Economics
Master's Thesis : Marketing

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ABSTRACT

The purpose of this thesis is to study to what extent visual features and the number of artists per song impact consumer interest and buying behaviour. Previous research on audiovisual congruency has mainly focused on the effect of audio accompaniment on images and videos in advertisements. Consequently, studies focusing on the effect of visual features on consumers' willingness to listen or buy songs are lacking. Exploratory interviews with established artists were conducted to get an insight in how the current music industry is shaped and what the main music distribution services are. A choice-based conjoint experiment (n = 250) in the context of visual marketing followed. Findings of the conjoint experiment show that a blue, naturally visualised cover and a song title that is perceived to be congruent with the cover colour, gives the highest likeliness for a consumer to become interested in a song and act accordingly. Additionally, findings suggest that the so-called 'featuring phenomenon' exists, regardless of the visual properties of a song. Skewed distributions in the characteristics of the respondents and a limited amount of examined attribute-levels make that these findings are only partly generalisable. This thesis contributes to make record labels or artists visually stand out and improve their recognisability and sales, without compromising creativity. Thus, this thesis helps marketing managers and cover designers to create more effective visual accompaniments for music.

Keywords: music, visual marketing, audiovisual congruency, consumer behaviour

1 INTRODUCTION

A good musician who is heard, for example, on the street or on the radio, will always be able to sell himself to listeners with his or her musical qualities. In today's age, when most artists are online, this is different. But how do you, as a musician, band or record label that is mainly active on Spotify or YouTube, ensure that a potential listener – who did not know about you yet – first arrives at your music? How do you get a listener who is unfamiliar with your musical qualities to start listening or even buy your music?

This is where marketing and music come together, as marketing is the key in reaching a larger group of potential customers. Especially in the current digital era, the amount of marketing opportunities is growing faster than ever before (Reza Kiani, 1998). Chaffey (2010) made a framework to improve digital marketing, consisting of four steps: reach, act, convert and engage. In the field of marketing, musicians or bands in the modern music industry are mainly involved with the 'act' step, as the first step of reaching the potential customer is done by platforms like Spotify, Soundcloud and YouTube, while in the last two steps of converting the lead to a customer and engaging with the audience are mainly done by the music itself.

What would then be the most convincing way to get the audience to click or interact with your music, instead of the millions of other songs which the aforementioned platforms feature? How to stand out from the crowd? Is it all about visual features? As that is about the only difference between your 'product' and the product of others, before the potential consumer clicks on your song or any other song. In this thesis, an answer to that question is searched for. On Spotify, the visual features mainly concerns cover artworks or a title of the song, while on YouTube, the 'thumbnail' or title of the music video is the first thing a potential customer sees.

2 RESEARCH QUESTION AND SUB-QUESTIONS

Creating a convincing cover or thumbnail and making up a good name for a song to get the consumer to 'act' can be quite challenging. This thesis is all about visual marketing in the modern music industry, in the form of artworks, as well as song titles. Therefore, the research question is:

To what extent do visual features and the number of artists per song in the modern music industry impact consumer interest and/or consumer buying behaviour?

In order to answer this main question, several sub-questions must first be answered. These sub-questions cover the different parts of the main research question and should help in understanding how the modern music industry is shaped, how successful artists visually draw the attention of fans over and over again, what drives an individual in clicking or even buying a certain song and what kind of artworks and song titles work best as a visual marketing strategy for different music genres. The sub-questions are split up in two theoretical sub-questions (TQ) and four empirical sub-questions (EQ):

TQ1: *How is the modern music industry shaped and who are the main distributors or streaming services out there?*

TQ2: *How do successful musicians or successful songs visually stand out from the crowd?*

EQ3: *What visual factors have the most impact among potential listeners or buyers in getting them to 'act'?*

EQ4: *Is there a significant interaction effect between the colour of a cover and the song titles?*

EQ5: *Does the 'featuring phenomenon' exist, regardless of a song's visual properties?*

EQ6: *Does the visualisation type of a cover (natural or artificial) impact the likeliness of potential listeners or buyers to 'act'?*

EQ7: *How can the most significant visual factors and song titles be combined into a successful visual marketing strategy for musicians, bands or record labels?*

3 RELEVANCE

This chapter of the thesis consists of two sections that explain both the social relevance of this study, as well as the scientific relevance of this study, apart from each other. First, in section 3.1, potential stakeholders of this study and visual marketing in the music industry in general are mentioned. Next, in section 3.2, the gap that this thesis should fill in existing scientific research is highlighted.

3.1 SOCIAL RELEVANCE

The social relevance of this research is in the fact that the growing music industry nowadays thrives in marketing (Stata Research Department, 2021). Musicians, as well as record labels and even streaming services could benefit a lot from this research, as this thesis will show them how to create a successful visual marketing strategy for their songs, albums, or platform.

This visual marketing strategy would then mainly impact the younger generation of consumers, as this generation is most reliant on using visual-based music streaming platforms, like Spotify on their smartphones (Pedrero-Esteban et al., 2019). Middle-aged and elderly people are, on the other hand, more likely to buy old-fashioned CDs (Feldman & Weir). The marketing strategy would need to convince the demand side of the modern music market – the consumer – to 'act'.

The demand side of the music industry is and will always be in charge. But the supply side can benefit from all of the new insights this thesis will provide, to gain as much demand as possible, apart from creating, releasing or offering the audio itself. This could not only have a big financial impact for artists or record labels, but also a social benefit by gaining a bigger audience and having more fans and shows all over the world.

With a big audience and shows all around the world, many different cultures play a role in marketing music. De Mooij and Hofstede (2011) state 'most aspects of consumer behaviour are culture-bond'. This also applies to visual marketing in the music industry. For instance, different colours have different meanings across cultures, resulting in different consumer reactions, as shown by Madden et al. (2000). On the other hand, some components of the music industry itself are not culture-bond. From Kubacki and Croft (2006) for example, it becomes clear that musicians across differing cultures seem unable or unwilling to close business and marketing related deals. In the meantime, government funding has reduced over the years. This could lead to the disappearance of non-commercial music as a whole. This thesis not only encourages artists with a management team or major record labels to improve their visual marketing strategy, but also makes music marketing feasible for smaller and unknown artists by presenting them with a clearly laid out visual marketing plan.

This is useful, as music marketing in general has become harder: there are fewer characteristics that can make a song stand out on a streaming platform like Spotify, compared to the conventional music distribution environment of physical stores. On the other hand, the role of purely visual marketing in music has grown to be more important with the rise of streaming platforms, as this has arguably become the only way to stand out in this online 'mass sale' environment.

3.2 SCIENTIFIC RELEVANCE

Research by Holt (2011) found that 'the distribution, presentation and communication about music has become more visual'. This indirectly means that visual marketing also plays – and will play – a more important role in the music industry.

In some studies, research has been done on co-creational marketing in the music industry, where both the consumer and the musician or band jointly promote the music. As a study by Gamble and Gilmore (2013) concludes, there are five levels of consumer control and five levels of consumer interest in terms of marketing for the music industry. But that study is about co-creational marketing, while this thesis will focus on the marketing in the music industry where there is no consumer control at all: visual marketing that comes from the musician or band itself, or a marketeer that was hired for this specific job.

Another study by Martin and McCracken (2001) found differences between two countries, in the sense of promoting brands or products within music videos or other visual marketing. This research compared music videos in the United Kingdom and New Zealand. The study concludes that music videos in the United Kingdom have more brand references and fashion imagery than music videos in New Zealand. However, this thesis will be about the visual promotion of the music itself, instead of promoting other brands or products within music videos. This makes the thesis relevant, adding new scientific insights to the world of visual music marketing.

4 LITERATURE REVIEW

This chapter is split up into four sections. The first section mentions relevant studies concerning visual marketing in general, while the second paragraph cites studies concerning music marketing in general. The third paragraph combines the aforementioned two and states additional studies that are interesting to the more specific field of visual marketing in the music industry. Section 4.4 compares the idea of this thesis with a marketing case study by Elberse et al. (2006), in terms of introducing statistics in music marketing.

4.1 VISUAL MARKETING IN GENERAL

Pieters and Wedel (2007) define visual marketing to be 'the strategic utilisation by firms of commercial and non-commercial visual signs and symbols to deliver desirable and/or useful messages to consumers'. Visual marketing is therefore about choices and every visual character of a product or service that leads to a consumer making a certain choice or altering behaviour towards a product or service. Concerning the amount of choices, Fasolo et al. (2009) state that consumers generally respond ambiguous to large choice sets in environments like the one of Spotify: attracted, but also deterred. While a larger set of choices usually means greater expected satisfaction, this could well lead to expectations that cannot be met (Fasolo et al., 2009; Lenton et al., 2008). However, as Iyengar and Lepper (2000) state, participants to their research reported to have a greater satisfaction with their choices when a limited amount of options was presented, compared to a larger set of choices (they researched 6 versus 24 or more choice options). Moreover, they found that having more choices is not necessarily more intrinsically motivating than having fewer choices and having more choice is associated with less purchasing (Iyengar & Lepper, 2000). In this thesis, the number of choices given to respondents in the conjoint experiment was considered with these theories in mind.

Choices, in terms of visual marketing, are made quick: according to Outing (2004), banner advertisements on websites are typically looked at for less than one and a half seconds, even when people gaze at the advertisement. According to Pieters and Wedel (2012), most advertisements (from newspapers and magazines to television advertisements) usually do not receive more than one single eye fixation, which is a maximum of 300 milliseconds during which the eye is still (Pieters and Wedel, 2000).

In another visual marketing-related study, Gaynor (1998) found that centralisation in visual marketing – concentrating the visual marketing department in one area of the business – in the context of fashion marketing in the United Kingdom, is of great importance for a number of reasons. According to respondents, centralisation of visual marketing has the benefits of 'communicating a cohesive brand image, differentiating the offer from the competition and integrating promotional effort across the brand' (Gaynor, 1998). In the end, musicians, as well as record labels and streaming services all have their own brand image, which consistency could improve when Gaynor's findings are more widely applicable.

Next to consistency, colour also plays a big role in visual marketing. As Jalali and Papatla (2016) state, colours have a major impact on consumer interaction. In their research – which was limited to colour only – they found that consumer click-rates were higher when a photo included a higher proportion of green colours. The importance of colours in marketing and shaping consumer behaviour is underlined by the research of Singh (2006), who states that colours can be used to 'increase or decrease appetite, enhance mood, calm down customers and reduce the perception of waiting time, among others'.

Contrary to the findings by Jalali and Papatla (2016), Biers and Richards (2005) found that the colour blue would raise consumer purchase intentions more than any other colour, when showed in advertisements. Babin et al. (2003) also found that the colour blue has a positive effect on consumer perception. In their research, they found that a blue store interior was associated with a more positive evaluation than an orange store interior. White et al. (2021) found, in a more recent study, that an analogous colour set between blue and green elicits a higher level of purchase intention towards web banner advertisements than other colour sets.

4.2 MUSIC MARKETING IN GENERAL

When platforms like YouTube were in their growth phase of the product life cycle, while platforms like Spotify did not exist yet, almost all music was sold in two formats: a digital form (on for example YouTube or iTunes) and a conventional form on CD or vinyl (Levitt, 1965). At that time, and in some cases still today, the marketing of both the digital form and the conventional form was bundled. Koukova et al. (2008) describe this way of advertising two or more forms of the same product as a package as 'product form bundling'. Nowadays, almost all music is sold or made available in an intangible format through online platforms. The rapid changes in the music industry to an online-only environment also shifted the marketing of music to be almost entirely digital, while previously, billboards in front of physical music outlets were used quite often (Ogden et al., 2011).

One of the biggest downsides of the increased online distribution of music is in piracy, that can partly be prevented by the indirect measure of decreasing price of the legal alternative (Sinha & Mandel, 2008). However, this measure would artificially devaluate the work of artists. Spotify and other streaming services have largely bypassed this problem by distributing the music of many different artists and introducing a subscription-based business model in the music industry. This makes Spotify one of the biggest music distribution platforms at the time of writing. Even though it is uncertain which channels will stay or take over in the future, Ogden et al. (2011) conclude that 'it will most likely involve technology and a greater degree of personalisation and value creation'.

4.3 VISUAL MARKETING IN MUSIC

To conquer these channels of personalisation and value creation, audiovisual congruency might play a big role. Lalwani et al. (2009) researched the topic of audiovisual congruency in advertisements and found the results they expected: a congruent product and music type in advertisements elicits favourable consumer responses. Rosenfeld and Steffens (2019) support the findings of audiovisual congruency on human behaviour, in the context of emotions in film. They found that audiovisual congruency in films increases the visually perceived emotions of the film, thus ensures that the viewer empathizes more with a film. Even though these studies are not about the promotion of music itself, these studies still imply that audiovisual congruency is important in marketing applications, due to the effect that it has on consumer behaviour.

While Lalwani et al. (2009) researched the effect of music on advertisements, not that much research has been conducted the other way around – into the effect of visual characteristics on music perception. Ebendorf (2007) is an exception to this, as she studied whether the mood and format of visual accompaniment in music videos affects consumers' perception of music in terms of acoustics and emotion. She found that flowing cohesive video stories have a significantly different effect on music perception, when compared to randomised changing images. On top of that, she states that music with a positively associated accompanying video was generally rated better.

Contrary to the visual studies mentioned before, Ordanini et al. (2018) studied a more linguistic topic in music marketing: the 'featuring phenomenon'. This phenomenon describes that songs featuring other artists increases consumer interest in songs. They found that songs featuring other artists have a bigger chance of getting into the top 10 than solo songs. This could have a big impact on the visual marketing strategy that will be presented in the end of this research and therefore needs to be studied in the context of visual marketing.

4.4 POLYPHONIC HMI CASE STUDY

A music marketing case that has some familiar elements, as compared to this thesis, is the case of Polyphonic HMI. This company made a technological tool that would estimate the 'hit potential' of a song. The tool is based on a database that can filter many different song characteristics. The company wanted to use this technology for so-called 'hit song science'. The idea was to sell the technology to record labels, who would then use it to estimate a song's potential to become a hit, based on the song's characteristics (Elberse et al., 2006).

As could be expected, some parties were impressed, while others were sceptical. The main reason why this technology did not succeed after all, was in the emotion and creativity that plays a key role in the music industry. If everything is measured against Polyphonic HMI's tool, this would result in a lot of comparable music and little creativity from the artist.

When one puts math in a creative business like music, it will face a lot of resistance. All emotion flows out if a band or an artist gets told that he or she has to make music according to an algorithm, in order to make it successful (Van der Linden, 2022). This would be a wrong step, as music is an important way to convey emotion, as Bodner and Gilboa (2006) show.

However, even though this thesis combines music and math, in order to make the likeliness for a consumer to 'act' as big as possible, the resistance that the technology of Polyphonic HMI faced would probably not apply to this thesis. After all, this research does not address the creative product itself (the music), but how it is sold. The emotion and creativity remains in the song itself, while the aim is to stand out and gain more attention for it through visual marketing.

5 EXPLORATORY RESEARCH

This section will provide extra information on the qualitative interviews that were conducted with the purpose of understanding the current music industry and to form an answer to the first two (theoretical) sub-questions. The interviews were semi-structured in nature, which means that the interviews consisted of open-ended questions and did not necessarily have a fixed order (Galletta, 2013). However, it was clear in advance what would, in broad terms, be asked. In the interviews, questions were asked about the modern music industry, the rise of streaming platforms, visual elements in song covers and their impact on attracting consumers and marketing in music. The full interview with Marc Bandecchi (Arcando) can be found in Appendix A, while the full interview with Idir Makhlaf and Thom Jongkind (Blasterjaxx) is transcribed in Appendix B.

These interviews roughly had two main objectives: getting insights for the empirical study and answering the first two theoretical sub-questions of this thesis. The main findings of the interviews are described in section 5.3.

5.1 INTERVIEWING MARC BANDECCHI

Arcando is a well-known name in the electronic dance music scene. His track 'Army', together with Besomorph and Neoni was viewed over 20 million times on YouTube alone. He worked together with the likes of Josh A, released tracks on record labels such as Revealed Recordings and successfully remixed famous songs like 'Whatever It Takes' by Imagine Dragons. On top of that, his single 'Rebel' was used in Netflix's 'Deaf U' series.

Arcando was a big name on Soundcloud when that platform was one of the biggest music distribution platforms when it came to monthly listeners and sales. He is an interesting artist to interview, given the fact that he saw that platform fall and had to adapt to other streaming services that were rising, like Spotify. He did this very well, gaining over a million monthly listeners on Spotify at the time of writing. The Arcando-interview is especially interesting for this study because of the artist's emphasis on Spotify, which is a platform that visually offers music in the format that is used in the quantitative part of this research. The interview with Arcando was conducted in a remote setting through a WhatsApp video call in Dutch. After taking the interview, it was transcribed it in English with Marc Bandecchi's knowledge and approval.

In the interview, it comes forward that the modern music industry is almost entirely based on online streaming platforms, with Spotify being the most important of them at the time of writing. Music distribution is mainly in hands of record labels that are usually genre-specific. The most important item in the interview was 'consistency'. Arcando values consistency in releasing music (once or two times a month), as well as in showing himself or his new music to his fans through different channels like Instagram or Twitter on a daily basis. He wants 'to be seen' regularly through these platforms, so that the Arcando 'brand' gains recognition. In visual terms, Arcando expects colour to be the most significant variable in this thesis. The transcription of the complete interview with Marc Bandecchi is attached in Appendix A.

5.2 INTERVIEWING IDIR MAKHLAF AND THOM JONGKIND

Famous deejay- and producer-duo Blasterjaxx gained recognition all over the world with their track 'Fifteen' back in 2015. They collaborated with various number-one deejays in the world, including Hardwell, Dimitri Vegas & Like Mike and Armin van Buuren (DJ Mag, 2022). The Blasterjaxx-duo has about a million Instagram followers, while attracting about three million monthly listeners on Spotify. They have played at all major dance festival stages in the world, including Tomorrowland and Ultra Miami. Since 2015, the duo launched Maxximize Records, a record label affiliated with Spinnin' Records – the most well-known dance music label in the world. Besides, they gained further recognition by creating the theme song of the 'Watch Dogs: Legion' game, which sold 1.9 million copies in the first three days after its release in October 2020 (Sinha, 2020).

The Blasterjaxx-duo are interesting subjects for this second interview, because of their unique experience being artists, while running a record label at the same time. Next to that, the size of their fan base and the amount of shows they have done over the years makes for a different, more professional, view of the music industry in general. The interview with Blasterjaxx was a conversational one in nature and originally held in Dutch, after which it was transcribed in English with their and their manager's knowledge and approval.

The interview gives more insight on how the current music industry is shaped from a label manager's perspective, as well as the importance of good streaming services like Spotify and Deezer. The deejay- and producer-duo also values the importance of consistency in marketing and all other facets of music. They explain that they think congruency between the title of a song and its visual aspects in the cover is important to deliver a consistent image. According to Jongkind and Makhlaf, visual consistency is also important across different songs that are released by the same label, to improve brand consistency and recognition of the record label. The duo also states that they use Instagram advertisements as a paid marketing tool, to stimulate the recognition of the music style and the Blasterjaxx-brand even more.

Another interesting idea they mentioned, is that having another artist working with them on a music piece increases consumer interest. This particular insight is, as stated in the literature review, backed by Ordanini et al. (2018), who state that combining artists of different genres significantly increases consumer interest in songs. As this could have a major impact on the success of the visual marketing strategy that will be presented in the end of this thesis, it was decided that this topic needs more extensive research. For that reason, one hypothesis will be devoted to the 'featuring phenomenon'. The transcription of the full interview with Idir Makhlaf and Thom Jongkind can be found in Appendix B.

5.3 MAIN FINDINGS OF THE INTERVIEWS

Coming back to the first theoretical sub-question, the interviews with Marc Bandecchi, Idir Makhlaf and Thom Jongkind have made clear how the current music industry is shaped and what the main music distribution services and streaming services are, at the time of writing. The music industry is fast-paced and tough. The distribution of music has multiple stakeholders, from the artists, through music labels and streaming services to the potential consumer. The main streaming service of this time is Spotify, while the first two stakeholders mentioned are trying to integrate the visual appearance of their songs consistently through other platforms like YouTube or Instagram, in order to build a relationship with the potential consumer.

In terms of visually standing out of from the crowd and the answer on the second theoretical sub-question, the interviewees did not give consistent answers. Where Marc Bandecchi thinks bright colours will have the biggest impact on visually attracting consumers, Idir Makhlaf thinks consistency plays a key role, while Thom Jongkind clearly thinks linguistic items – including track names and the amount of artists working on a song – make the biggest difference. The inconsistency between these answers could partly be explained by the fact that both Arcando and the Blasterjaxx-duo never had an external company or a marketing manager review the importance of these visual attributes in attracting new consumers or stimulating existing consumers to 'act'. The Blasterjaxx-duo even stated that they did not let a marketeer look into this on purpose, to stay creative with their song covers and music videos.

The different findings in the interviews, when it comes to the second theoretical sub-question of this research, imply that there are multiple ways to visually stand out and get your message across in the modern music industry. The quantitative part of this thesis will give more insights on what visual and linguistic items have the most significant effect on a consumer's decision whether to 'act' or not.

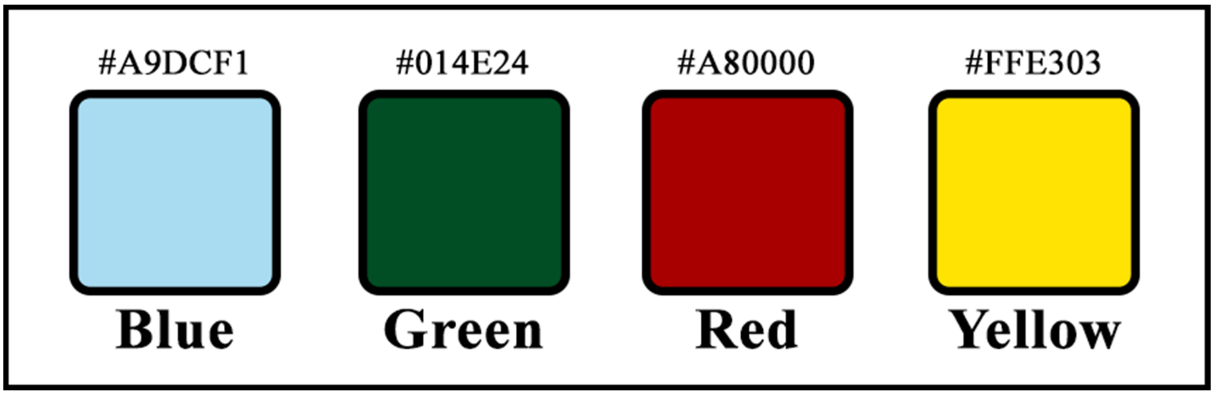
6 HYPOTHESES

For the quantitative research of this thesis, four hypotheses that follow from the literature review and the interviews held with Marc Bandecchi (Arcando, Appendix A) and Idir Makhlaf and Thom Jongkind (Blasterjaxx, Appendix B), three well-known names in the electronic dance music scene, are presented below.

As Jalali and Papatla (2016) stated that colour has a big impact on consumer interaction, while Marc Bandecchi (Appendix A) expects colour to be the most significant visual factor in this thesis, it seems obvious that colour plays a major role in consumers' choice of whether or not to 'act'. Singh (2006) supports this and states that people usually form an opinion about a product within 90 seconds, while 60% to 90% of this opinion could be based on colours alone. This makes colour being one of the most important factors for product choice, when it comes to fast decisions. For the sake of simplicity, the quantitative research in the thesis will be limited to the four basic/primary colours, depicted in Figure 1 below.

Figure 1

The four colours that will be used in the quantitative part of the thesis and their hexadecimal code.



White et al. (2021) found that an analogous colour set between blue and green elicits a higher level of purchase intention and attitude towards web banner advertisements than other colour sets, while research by Babin et al. (2003) showed that participants rated the colour blue to be more likable, resulting in higher purchase intention levels, than other colours. Biers and Richards (2005) support this theory even further and state that people on average are more positive towards advertisements with blue as a primary colour. However, Taylor et al. (2013) state that colour preferences are not universal, potentially meaning that there is a probability of ambiguous or high variance responses when it comes to colour in the conjoint experiment.

Considering covers and music video thumbnails to be advertisements of songs, a logical first hypothesis for this thesis would be:

H1: *The most significant variable that has an impact on the likeliness to 'act' will be colour, with blue being the most positively influencing colour among them.*

The second hypothesis follows from the previous study on the 'featuring phenomenon' by Ordanini et al. (2018), discussed in chapter 4. As Idir Makhlaf and Thom Jongkind (Appendix B) also feel like this phenomenon exists, it is interesting to study this in the context of visual marketing for music.

H2: *Music featuring more artists increases overall interest in a song, increasing the probability of a consumer to 'act', regardless of the visual properties of the song.*

Covers of songs are usually based on either natural visualisation – manmade photographs – or artificial visualisation, using advanced computer programs. According to Athitsos et al. (1997), a few basic differences between natural visualisation (photographs) and artificial visualisation (graphics) are easily noticeable. For example, colour transitions, as well as structure transitions in photographs are usually smoother, as compared to graphics, as objects tend to have texture. As a result, photographs contain more colours than graphics. Next to that, photographs often hold less saturated colours (Athitsos et al., 1997). This is endorsed in a study by Khalsa and Ingole (2014), who state that natural images are smoother in terms of colour and brightness transitions, compared to artificial images, based on a so-called 'gray histogram'.

Research by Kardan et al. (2015) shows that people are attracted by smoothness, when it comes to visualisation. This is true in terms of colour-related regularities (diversity in saturation), as well as structure-related regularities (less straight edges). As Athitsos et al. (1997) and Khalsa and Ingole (2014) state that natural images are smoother in terms of both colour transitions and structure transitions, while Kardan et al. (2015) states that people are visually attracted by smoothness, a third hypothesis for this research is:

H3: *Natural visualisation of a cover will attract more (potential) music consumers than artificial visualisation does.*

As Idir Makhlaf and Thom Jongkind (Appendix B) value congruency between the audio of the song, the visual representation of the song and its title, while Lalwani et al. (2009) conclude that audiovisual congruency – including colour – in product and music type elicit stronger consumer responses, it seems to make sense that consumers would be more likely to have a clearer positive or clearer negative attitude towards a coherent visual whole.

On the other hand, according to social judgement theory by Sherif et al. (1965), people will go as far as rejecting information that is incongruent and falls outside the acceptance range.

A study by Dahlén et al. (2005) supports these findings and states that incongruency can lead to consumers ignoring the advertisement.

As multiple studies show that congruency in advertisements results in a stronger attitude towards that advertisement, while incongruency could lead to consumers ignoring the details and differences between options, a fourth hypothesis that follows from this, is:

H4: *There is a significant positive interaction effect between song titles and the 'colour' variable, resulting in a higher predictive power of 'colour' on the likeliness to 'act' when the song title and the colour of the cover are congruent.*

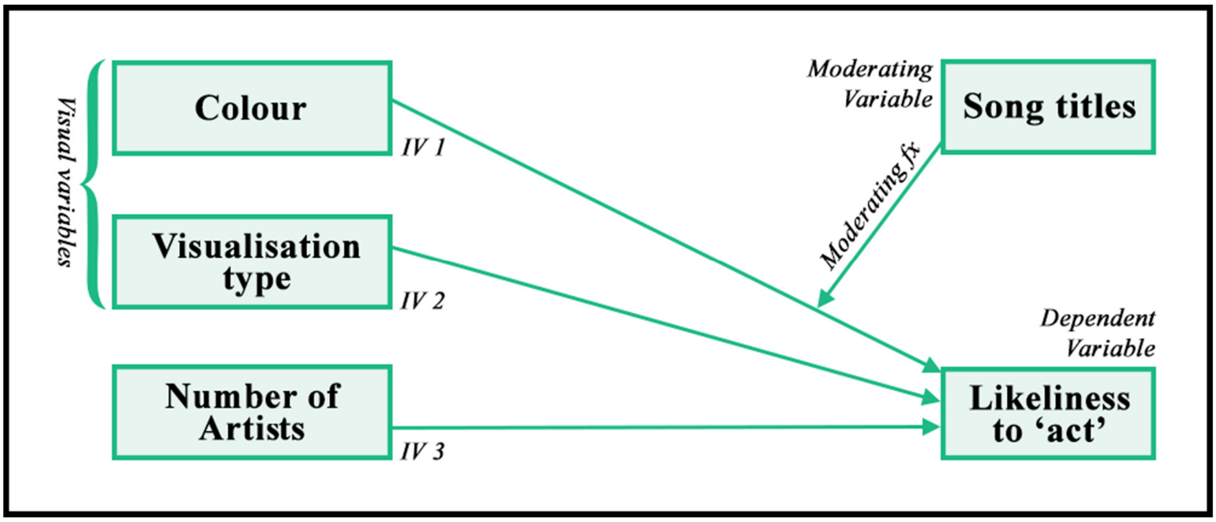
7 CONCEPTUAL MODEL

The conceptual model of this thesis, that can be seen in Figure 2, is relevant for both empirical sub-questions three, four, five and six, as well as indirectly relevant for sub-question seven. The data that will be gathered for sub-questions three, four, five and six and the resulting logistic regression analyses should be able to not only measure the importance of each variable that is used in the regression, but also whether or not a song title moderates the initial effect of colour on the likeliness of buying or listening (to 'act'). According to Lance (1988), a moderator variable is a 'measured variable, across whose values the relationship between two or more other variables varies'. For this research, it will be investigated whether or not there is a significant interaction effect between the titles of music pieces and the colour of the cover of these songs.

Two analyses will be conducted on the same data, where one includes the possible interaction effect (fitting song titles with colour) and one does not. In theory, this means two different models are used on the same data. In the visual representation of the conceptual model, this was not taken into account, as the models only vary in the moderating variable: one model includes it, and one does not. In the second analysis, the moderator effect can be estimated while taking the main effects into account. As a measure to evaluate the performance of both regression models, the Bayesian Information Criterion (BIC) by Schwarz (1978) is used. By introducing more parameters (like the interaction effect of fitting song titles with the colour of a cover) to a model, the BIC could increase or decrease as the model has more or less scientific predictive power. Generally, adding parameters that matter to the value of the dependent variable decrease the BIC measure and make for a better predictive model, but with the addition of every variable, an increasing penalty is introduced by the criterion (Schwarz, 1978).

Figure 2

Conceptual model: analysis to measure the impact of multiple variables on the likeliness to 'act'.



Note: main effects of colour (independent variable 1), visualisation type (independent variable 2) and the number of artists (independent variable 3) on the likeliness to 'act' (the dependent variable) are estimated, along with the moderation effect of a fitting song-title on the colour of a song cover.

8 METHODOLOGY AND DATA CHARACTERISTICS

This chapter is split into three sections, from which the first one explains the general methods that are used to answer the seven sub-questions of this thesis. The second section consists of a pre-test, that is used to reduce the bias towards details that are not of interest in the variables that are used in the conjoint experiment. The last section includes two sub-sections with information about the design of the conjoint experiment and the gathered data for the conjoint experiment.

8.1 METHODS TO ANSWER THE SUB-QUESTIONS

The first two (theoretical) sub-questions have been answered in section 5.3 with the main findings of the qualitative interviews with Marc Bandecchi, Idir Makhlaf and Thom Jongkind. These answers will be reiterated in the conclusion of this thesis, together with the answers to all other sub-questions (chapter 11).

The third sub-question is one of an empirical nature. This will be researched by distributing a questionnaire in the form of a choice-based conjoint experiment. This conjoint experiment would have an asymmetrical orthogonal design, as it will have quite a few different levels within the four attributes: colour, natural vs artificial visualisation, number of artists and song titles (Addelman, 1962). By including song titles in the choice-based conjoint experiment, the questionnaire can also cover empirical sub-question four. As almost everyone has some sort of connection with music on digital platforms, it should not be distributed to a specific group, but rather as random as possible to as many respondents as possible.

For sub-question four, the song titles in the choice-based conjoint questionnaire will, in a second data-analysis, be linked to colour, to see whether there is a significant interaction effect between the song title of a track and its cover-colour. That way, the research will also take a possible interaction effect between the linguistic elements and the visual element of colour of a song's cover into account. From the interviews with both Marc Bandecchi, as well as Idir Makhlaf and Thom Jongkind, it becomes clear that they all think this interaction effect exists. In the end of the research, it is shown whether or not this effect actually exists. Both sub-questions three and four will be analysed with a logistic regression analysis, because after all, the research is about the likeliness (i.e. a probability) of the consumer buying or having interest (Aldrich & Nelson, 1984).

One of the attributes is the number of artists, which has two levels: one or two artists. Including either one or two artists per choice option in the questionnaire will shine more light on the 'featuring phenomenon' – that Ordanini et al. (2018) researched – and the importance of collaborations in marketing in the modern music industry. This will lead to a clear answer to empirical sub-question five.

For sub-question six, it will be studied whether the natural visualisation of a song cover holds different consumer responses, as opposed to an artificially visualised cover. To research this, both natural as well as artificial images will be used in the conjoint experiment (section 8.3), in order to be able to spot differences between these visualisation types. To get a better understanding of what people in general perceive to be 'natural' and 'artificial', a pre-test is conducted (section 8.2) and analysed in SPSS.

To process the data of the questionnaire for empirical sub-questions three to six and the choice-based conjoint experiment, SAS JMP, a statistical program in which the conjoint experiment can be built and analysed, will be used.

The answer to the last sub-question can be formed by reviewing all data from the previously answered sub-questions, in combination with strategic marketing theories by Porter and Booms and Bitner. The most popular music distribution platforms, as well as the visual factors and song title properties that are seen as most important by potential listeners or buyers of music, all have their impact on the success of a visual marketing strategy for musicians or record labels.

8.2 PRE-TEST

According to Hu (2014), 'Pretesting is the stage in survey research when survey questions and questionnaires are tested on members of target population/study population, to evaluate the reliability and validity of the survey instruments prior to their final distribution'.

In this research, a pre-test (n = 36) is used to make sure that there is as little as possible bias towards details that are not of interest in the independent and moderating variables that will be used in the questionnaire. As can be found in chapter 7, the independent variables of interest in this study are the number of artists, the visualisation method (natural versus artificial) and the colour (blue, green, red and yellow, as depicted in Figure 1). The moderating variable of interest is the title of a song (fitting versus non-fitting with the colour of a song cover).

To study the impact of the number of artists (one or two) and research *H2*, it has to be made sure that there is no general bias in the preference towards specific artist names. For that reason, respondents of the pre-test are asked to rate the likability of six different artist names, from which only the four most similarly rated names will be used in the questionnaire. This way, the effect of the number of artists on the likeliness to act is measured with a minimal bias towards particular artist names. The set-up of this part of the pre-test can be found in Figure C1 in Appendix C. As for the results, multiple one-way analyses of variance (ANOVA analyses) are conducted to make sure that there are no significant differences in artist name-likability for the artist names to use in the questionnaire research (section 8.3). Descriptive statistics for the artist name-likability scores per artist are shown in Table C1 in Appendix C, while the descriptive statistics of the total name-likability scores of all artist combined are shown in Table C2. Table C3 shows the first one-way ANOVA that was conducted to see if there is a difference between the likability-means when all six artist names are used in the questionnaire. The analysis shows that the F-statistic, in this case, is higher than the critical value in the F-table, which means that one or more of the artist names likeability-scores differs significantly in mean (Moore et al., 2016).

As this ANOVA only tells that one or more of the artist names differs significantly in mean – and not which one(s) – a logical next step is to remove the artist name whose likability score deviates furthest from the total mean score obtained by all artist names together (Table C2). As can be seen in Table C1, this would be 'Hozier'. The results of the next analysis can be found in Table C4, which shows another one-way ANOVA, this time without 'Hozier'. While the F-statistic got closer to the critical value in the F-table, the differences between one or more artist names' likability-scores are still significant (Moore et al., 2016). Removing artist name 'Grimes' – following the same method and Table C1 and C2 – gives the desired result of four artist names from which the likability score-means do not significantly differ from each other, as shown in the one-way ANOVA in Table C5. Here, the F-statistic is lower than the critical value that corresponds with the appropriate degrees of freedom and an alpha of 0.01 in the F-table (Moore et al., 2016). Thus, for the choice-based conjoint questionnaire, four artist names – 'Lyeoka', 'Naturally 7', 'Austra' and 'Flume' – will be used.

To verify these findings and to double check whether artist names 'Hozier' and 'Grimes' are the only ones that are significantly different in likability rating, a post-hoc test was conducted. As Armstrong (2014) states that the Bonferroni correction is the most popular method to correct p-values and control for Type I errors, this method is used to check for significant differences between the different artist names in terms of their likability rating. Table C6 in Appendix C shows that the results of the Bonferroni post-hoc test are identical to the results that were previously found, meaning artist names 'Lyeoka', 'Naturally 7', 'Austra' and 'Flume' can be considered equally likable, while 'Hozier' and 'Grimes' have a significantly different likability rating.

With regard to the visualisation of the covers that will be used in the choice-based conjoint questionnaire, this study distinguishes between natural and artificial options. In chapter 6 of this research, studies by Athitsos et al. (1997) and Khalsa and Ingole (2014) concluded that most of the distinctions between natural images (photographs) and artificial images (graphics) originate from colour differences and transitions. However, for the pre-test of this research, monochrome images were used. This is because of the fact that, in general, some colours can be perceived as more 'natural' than others, affecting the outcome of the perceived naturalness. As an example, vegetables like lettuce and avocado are increasingly getting colour dyed green, to influence the consumer's perceived naturalness (Lakshmi, 2014).

Not including colour in the covers of the pre-test therefor has the function to see whether the different images (natural and artificial) can be clearly distinguished from each other, even without colour differences. The natural versus artificial rating of the pre-test respondents should then mainly be based on other factors that Khalsa and Ingole (2014) mentioned in their study, such as brightness and structure transitions and the recognition of natural elements. In this thesis, the intention is to measure the effect of colour and visualisation (natural versus artificial) apart of each other. Thus, these effects are disconnected as much as possible from each other.

Important to note is that each artificial-natural rating question also included a component where the respondent had to rate the likability of the image, to control for biases within the natural and artificial groups that would later be used for the questionnaire research. The design of one of the questions asked in this part of the pre-test is shown in Figure C2 in Appendix C.

To make sure that the different pictures are either seen as 'more artificial' or 'more natural' than average, Table C7 shows a one sample t-test to compare the mean natural rating per picture – named 'A' to 'N' – to the scale mean of three. The t-test shows that the natural versus artificial ratings of all used pictures in the pre-test differ significantly from the scale mean, with pictures C, E, F, G, I, L and M rated more natural than average and picture A, B, D, H, J, K and N rated more artificial than average. Table C8 links the different pictures that were used in the pre-test to the letter of that picture, as given in Table C7, while also describing the respondents' perceived naturalness per picture.

The descriptive statistics of the likability rating of each picture is shown in Table C9. To make sure that there is no bias in the likability within the group of different natural pictures, one-way analyses of variance are conducted to research mean differences between the different natural pictures. As shown in Table C10, when using all natural rated pictures, the F-statistic is higher than the critical value, meaning there are differences in the mean perceived likability of one or more natural pictures. Following the same method used to reduce the amount of artist names until there are no significant differences in likability, picture G was first removed from the analysis. This picture has the most deviant mean likability score, when compared to the other natural pictures, as can be seen in Table C9. The one-way ANOVA for the mean differences in likability of the natural pictures, without picture G, is shown in TableC11. When picture G is removed, results show that the F-statistic is lower than the critical value that corresponds with the appropriate degrees of freedom and an alpha of 0.01 in the F-table (Moore et al., 2016). This means that for the choice based conjoint questionnaire, picture C, E, F, I, L and M will be used to represent 'natural' pictures.

To make sure that there is no bias in the likability within the group of different artificial pictures, similar analyses were conducted. Table C12 shows the one-way ANOVA that results from using all artificial rated pictures and the corresponding F-statistic that is higher than the critical value. Thus, picture B was removed, as this picture has the most deviant mean likability score, when compared to the other artificial pictures. Table C13 represents the one-way ANOVA for the mean differences in likability of the artificial pictures without picture B. In this analysis, the F-statistic is lower than the critical value, meaning pictures A, D, H, J, K and N are used to represent 'artificial' pictures in the choice based conjoint questionnaire. The likability differences between both groups (natural and artificial) and the impact this has on the likeliness to 'act', is to be estimated in the choice-based conjoint analysis of the questionnaire.

To verify whether the likability means of both natural pictures C, E, F, I, L and M, as well as artificial pictures A, D, H, J, K and N are indeed not significantly different, while the likability means of G and B deviate from respectively the other natural and artificial pictures, a paired samples t-test was conducted. As there are many comparisons – in terms of likability – between all of the natural rated pictures and between all of the artificial rated pictures, a paired samples t-test is the best way to compare the likability means of the different natural-pairs and artificial-pairs. The Bonferroni correction was not used here, as not all pairs are essential for this thesis. For example, it is not of interest whether a given natural image has a mean likability rating comparable to the mean likability rating of a given artificial image or not. In Table C14, the paired samples t-test is shown, including Cohen's D for all pairs. As the paired samples t-test is only used to evaluate previous findings, even though some significant differences are found between other picture-pairs, B and G remain the only removed pictures from the used set in the conjoint experiment. Table C14 shows that these two pictures have the highest amount of significant mean likability differences with the other pictures in their groups – natural or artificial. To emphasise, picture B and G are the only two pictures that have an average Cohen's D of close to 0.5 or higher, as shown in Table C15. This means these two pictures are the only two pictures in this thesis that are considered to have a medium or slightly bigger effect size on average, according to Cohen (1988).

For the independent variable of colour, no specific adjustments are made in the pre-test to evaluate its reliability or validity, as the four basic colours that were used (Figure 1), are clearly distinguishable and not influenced by other independent variables used in this research. To research the impact of fitting versus non-fitting colours with certain song titles, the pre-test first has to indicate what is perceived as 'fitting' or 'non-fitting' by the target population. To determine which song title fits which of the aforementioned colours and which song title is specifically non-fitting with one or more of these colours, pre-test respondents are asked to 'match' made-up song titles to one or more of the four primary colours used in this research. The set-up of this part of the pre-test is shown in Figure C3 in Appendix C.

Table C16 shows the results to this question, where respondents were allowed to match multiple colours with every song title. Taking 35 responses into account (one response was removed), a score of 25 or higher is seen as a relatively high score, meaning that specific colour matches a certain song title well. A score of 6 or lower is seen as a relatively low score, meaning that specific colour does not match a certain song title well. Scores of 25 or higher will be used to link a song title to an obtained (by JMP, see section 8.3) colour in the fitting-only questionnaire, while scores of 6 or lower will be used to link a song title to an obtained colour in the non-fitting questionnaire. The set-up of the conjoint experiment will be explained in more detail in the next section.

The performed pre-test does not erase the possibility of personal rare biases towards certain options in the choice-based conjoint questionnaire, such as a respondent who will always pick the option on the right side of the screen or a respondent who, on purpose, always picks his or her least favourite option. That is a limitation that will persist in this study.

8.3 CONJOINT EXPERIMENT

In this section, the choice-based conjoint experiment is explained in detail. For clarity, this section is divided into two sub-sections, from which the first one discusses the conjoint experiment design and the second one discusses the gathered data and the sample size.

8.3.1 DESIGN OF THE CONJOINT EXPERIMENT

In the conjoint experiment of this thesis, every participant sees eight choice sets in a randomised order and is asked which song they would most likely listen to. Per choice set, three options are given, which varied on three attributes: colour, visualisation type and number of artists.

Three choice options per choice set is not considered to be a large set of options. While Schwartz (2004) suggests that having choice is better than having no choice at all, he also states that more is not always better. Iyengar and Lepper (2000) found that having more choices is not necessarily more intrinsically motivating than having fewer choices and having more choice is associated with less purchasing – less ‘acting’. According to Schwartz et al. (2002), there is generally two types of consumers: consumers who pick the first option that seems to have satisfactory benefits, called ‘satisficers’, and consumers who strive for the very best choice, called ‘maximizers’. To capture both types of consumers, three choices per choice set does not seem to be too much, whilst being a sufficient amount to capture the effects of the different attributes. In Table 1, the used attributes and their levels are shown.

Table 1

The attributes and their corresponding levels used in the conjoint experiment.

Attribute	Level 4	Level 3	Level 2	Level 1
Colour	Yellow	Red	Green	Blue
Visualisation			Artificial	Natural
Number of artists			1	2
Song titles			Non-fitting	Fitting

Note: the ‘song titles’ attribute is analysed through a between-subjects design, while the other attributes are analysed through a within-subject design. Hence the difference between this table and the table in the conjoint experiment design in Figure C8 (Appendix C).

To generate choice sets for the questionnaire, SAS JMP's 'design of experiments' section is used. To create a reliable conjoint experiment with the three attributes 'colour', 'visualisation' and 'number of artists', prior means need to be entered into the experiment design. In order to research the fourth attribute and the moderator effect, participants are randomly assigned to either a 'fitting' questionnaire where song titles fit the colour of a cover, or a 'non-fitting' questionnaire, where there is no song title-colour fit.

As Huber and Zwerina (1996) state, setting relevant prior parameters to increase the utility balance of choice designs will also make choice designs statistically more efficient. Moreover, they found that utility-balanced designs can reduce the number of respondents needed to achieve a certain error level by 10 to 50%. Introducing a more balanced utility in the design will make sure JMP generates less 'obvious choices', meaning choice sets that are uninformative.

Prior means of -0.50, -0.25, 0.25 and 0.5 (the reference attribute-level will make the total effect of each level for an attribute exactly 0) are assigned for respectively the 'yellow', 'red', 'green' and 'blue' colours. Also, prior means of -0.5 and 0.5 are set for respectively the 'artificial' and 'natural' attribute-levels in the 'visualisation' attribute and respectively the '1' and '2' attribute-levels in the 'number of artists' attribute. These prior means give an estimation of the probability that a respondent chooses one option over the other alternatives. For example, the prior estimated probability of a respondent choosing a blue coloured cover over a yellow coloured cover is $e^{0.5}/(e^{0.5} + e^{-0.5}) \approx 0.73$. All prior estimated probabilities of a respondent choosing a certain attribute-level over another attribute-level are given in Table C17 and are weakly informative (Gelman, 2006). All prior means are based on colour theories by Jalali and Papatla (2016), Babin et al. (2003), White et al. (2021) and Biers and Richards (2005), the structural higher mean likability rating for natural pictures over artificial pictures in the pre-test (Table C9) and the research of Ordanini et al. (2018) on the 'featuring phenomenon'. The full design of the conjoint experiment in JMP, including the set-up of the prior means of all attribute-levels, is shown in Figure C7 in Appendix C.

From this input in JMP, the output that can be found in Figure C8 was obtained. Even though two questionnaires ('non-fitting' and 'fitting') will be used, this conjoint design output will be used for both.

The artificial pictures that are used for the conjoint experiment are all used twice, except for one that was only used once, while the natural pictures that are used for the conjoint experiment are all used twice, except for one that was used three times. The reason for this is that the JMP output in Figure C8 assigned 11 artificial visualised pictures and 13 natural visualised pictures to the total experiment. All pictures are used twice on average and distributed as evenly as possible, not using the same picture multiple times in one choice set. This way, every respondent will see every picture used at least once and a maximum of three times, which ensures that there is as little bias as possible towards a certain picture that would appear (much) more often or (much) less often than another picture.

The different four artist names used are also distributed as evenly as possible. It is ensured that as little as possible of the same imaginary 'collaborations' between artists occurred and every artist name has about the same amount of appearances within both questionnaires. By distributing artist names as well as the pictures used evenly, rather than randomly within the questionnaires, internal validity is ensured as much as possible. Distributing these options randomly would increase the chance of seeing one of the artist names way more often than the other one, potentially compromising internal validity. Also, given the fact that pre-test respondents rated the pictures and artist names that were used in the conjoint experiment about equally, an evenly distributed questionnaire in terms of these items seems the most valid option.

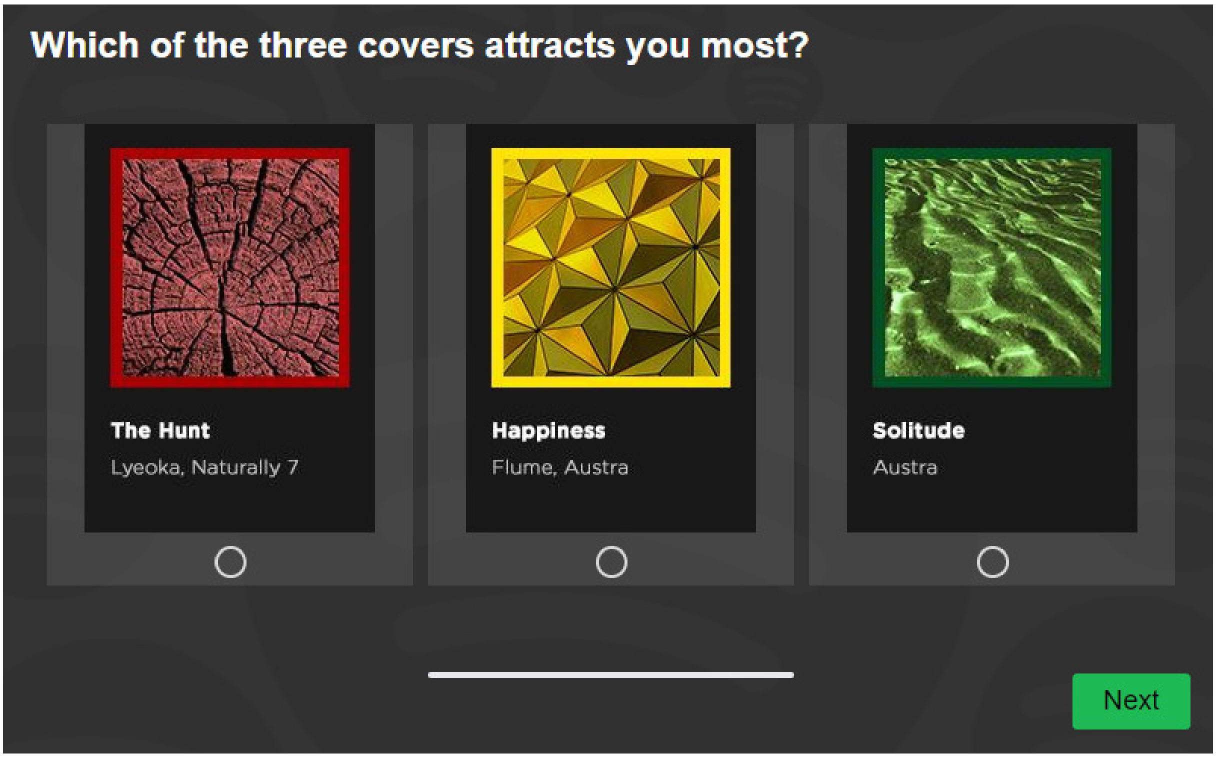
To capture the possible moderating effect with the questionnaire, half of the respondents will be randomly assigned to a 'fitting-only' questionnaire, while the other half of the respondents will be randomly assigned to a 'non-fitting-only' questionnaire. That way, *H4* can be measured. Song titles that were matched to a certain colour at least 25 times by 35 pre-test respondents were used in the 'fitting-only' questionnaire. Every song title is used only twice and the 'fitting-only' questionnaire has the highest total 'fitting-score'. For the 'non-fitting-only' questionnaire, only song titles that were matched to a certain colour by a maximum of 6 out of 35 respondents were considered, minimizing the total 'fitting-score', while not using song titles more than two times for this questionnaire. In Table C16, colours and song titles that were linked 25 times or more are coloured green, while colour-song title matches that were only considered by 6 or less pre-test respondents are underlined.

To minimise order bias – the bias that could arise from the order in which the questions in a questionnaire are presented – question order randomisation is applied to both surveys (Ferber, 1952). Also, assigning respondents to one of the two surveys is done random but evenly, so that the same amount of respondents will be assigned to either the 'fitting-only' or the 'non-fitting-only' questionnaire.

An example question in the conjoint experiment is shown in Figure 3 below. This is a question of the 'fitting-only' questionnaire, where the colours and song titles are matched. The example question in Figure 3 corresponds to the first choice set in JMP's output (Figure C8), where the first option consists of a red, natural background including two artists, the second option consists of a yellow, artificial background including two artists and the third option consists of a green, natural background and is a supposedly a solo song. Every respondent was asked to choose between three alternatives eight times. After answering these conjoint questions, the respondent was asked for his/her age, gender (optional), whether or not the respondent has ever used Spotify before and what the respondent's preferred music distribution service (MDS) is.

Figure 3

Example question of the conjoint experiment.



With the conjoint experiment, the following statistical model (Equation 1), which includes all variables that are used in this thesis, is estimated:

$$\begin{aligned} U_i = ß_0 + ß_1 \times \text{Yellow}_i + ß_2 \times \text{Red}_i + ß_3 \times \text{Green}_i + ß_4 \times \text{Artificial}_i + ß_5 \times [1]\,\text{Artist}_i \\ + ß_6 \times \text{Fitting}_i \times \text{Yellow}_i + ß_7 \times \text{Fitting}_i \times \text{Red}_i + ß_8 \times \text{Fitting}_i \times \text{Green}_i + \varepsilon_i \end{aligned} \quad (1)$$

8.3.2 SAMPLE SIZE AND THE REMOVAL OF OUTLIERS

For sample size, Rich Johnson's rule of thumb for choice-based conjoint sample sizes was used, as shown below in Equation 2 (Orme, 2020).

$$n \geq 500c/(t \times a) \quad (2)$$

Where n is the number of respondents, t is the number of questions, a is the number of alternatives per choice set and c is the largest number of levels for any one attribute. In this conjoint experiment, $n \approx 83$ represents the minimal amount of respondents to get sufficient results, according to Johnson's rule of thumb. However, as was stated by Orme (2020), this rule of thumb represents the absolute minimum and at least twice this amount should be used to get the most reliable results. To be on the safe side, in this thesis, the aim was to collect over 200 responses. This target has been far exceeded, as 268 responses were collected.

In order to be sure that every respondent was comfortable in this Spotify-imitated environment and did not get distracted from the experiment because the setting may have been unclear to them, the first outliers that were removed were seven respondents that stated to have never used Spotify before. Also, to cover for a possible response bias – where respondents click through the survey as fast as possible, without answering the questions to the best of their ability – every answer was timed. In total, 11 outliers were removed that contained answers that were submitted the quickest overall and fell outside the lower boundary of the 2σ-range from μ, taken from the quickest 10 responses of each question, as shown in Table C18 in Appendix C. This means these 11 outliers are in the quickest 5% of the total studied quickest 10 responses per question (Moore et al., 2016). It is important to keep all other relatively quick responses, as in section 4.1, Outing (2004) and Pieters and Wedel (2012) showed that most visual choices are made within one and a half second and only receive one eye fixation.

From the 268 collected responses, a total of 18 outliers were removed. This leaves a final sample size of 250, which is three times the suggested amount of respondents by Rich Johnson's rule of thumb.

9 RESULTS AND DISCUSSION OF THE CONJOINT EXPERIMENT

In Figure C4 in Appendix C, it was shown that from the 250 respondents who participated in the conjoint experiment, over 50% was between 20 and 29 years old. Also, the sample had slightly more male respondents than female respondents, as shown in Figure C5. Furthermore, Figure C6 shows that 148 out of 250 respondents used Spotify as their preferred music distribution service (MDS). Of the respondents that indicated to use another MDS, some used Apple Music and others preferred the radio.

To conclude the results of the conjoint experiment, the same order as the order of the hypotheses in chapter 6 was followed. Therefore, first the impact of colour is discussed, then the results corresponding with the number of artist are described, after which the results of the visualisation type are considered, to conclude this chapter with the results of the interaction effect between song titles and the colour of a cover.

To begin with, results of the conjoint experiment indicate that colour has the biggest impact on the consumers' likeliness to act, as the relative importance of this attribute, compared to the other attributes, is 0.624, as shown below in Table 2 and Table 3. This means consumers will base their choice mainly on colour, while the visualisation type, as well as the number of artists involved also play a role in consumers' choice to click a song.

Table 2

Importance of the three main attributes.

Main attribute	Range	Importance
Colour	1.888	0.624
Visualisation	0.687	0.227
Number of Artists	0.451	0.149
Total effect	3.026	1

Note: importance is weighted by calculating the range of the marginal utility of each attribute, taken from the effect marginals (Table 3 below) and dividing this range per attribute by the total effect range.

Table 3

Effect marginals of the conjoint experiment.

Marginal probability	Marginal Utility		Colour
0.1405	-0.3083		Yellow
0.0891	-0.7645		Red
0.1818	-0.0511		Green
0.5886	1.1239		Blue

Marginal probability	Marginal Utility		Number of Artists
0.3891	-0.22559		1
0.6109	0.22559		2

Marginal probability	Marginal Utility		Visualisation
0.3346	-0.34367		Artificial
0.6654	0.34367		Natural

Blue indeed is the most positively influencing colour among all colours, as its marginal probability is very high, compared to the marginal probability of the other colours, as shown in Table 3. Comparing an option with a blue cover to three other options with a red, yellow and green cover, while all other attributes are kept equal across these options, the chance of a consumer picking the option with the blue cover is 58.86%.

However, the first hypothesis, which states that colour is the most significant variable that has an impact on consumers' likeliness to 'act', is not fully supported by the data. Colour is not the most significant attribute resulting from the data when taking all variables, including the interaction effect, into account. Although colour has the biggest effect and is a significant attribute, visualisation is the most significant one among the main effects, when the interaction effect is included in the model (Table 4).

Interestingly, when running the analysis for main effects only, colour would be the most significant attribute among all. This can be seen in Table 5 below. Therefore, to a certain extent, the first hypothesis seems to be supported by the data. Yet, note that the Bayesian Information Criterion (BIC) increases when removing the interaction effect out of the equation, meaning the predictive power of the model with the interaction effect included is better than the predictive power of the model without the interaction effect taken into account. In summary, this means that the first hypothesis is not fully supported by the data in the better of the two models. The fact that all of the studied effects are very significant, shows that visually standing out is a story with several roads leading to the same objective.

Table 4

Effect summary of the conjoint experiment, taking all effects of interest into account.

Source	LogWorth	LogWorth (visual)	Sig.
Visualisation	36.576		<.001
Fitting or Non-fitting*Colour	20.558		<.001
Colour	20.340		<.001
Number of Artists	15.394		<.001

Note: a LogWorth of 2 (the green line) corresponds to an alpha level of 0.01. The bars show how significant each variable is, compared to the other variables. Even though the effect of all four variables are significant, it is interesting to note that the effect of visualisation is the most significant one of all.

Table 5

Effect summary of the conjoint experiment, only taking the main effects of the thesis into account.

Source	LogWorth	LogWorth (visual)	Sig.
Colour	113.426		<.001
Visualisation	34.274		<.001
Number of Artists	14.734		<.001

One of these roads would be in the amount of artists that have worked on a music piece. Despite the fact that it was not studied what the effect of having three or more artists collaborate on a music piece would be, it seems likely that the number of artists involved – to a certain extent – has a significant positive effect on the consumers' likeliness to act. Comparing an option with two artists to an option with one artist, while all other attributes are kept equal across these two options, the chance of a consumer picking the option with two artists is 61.09%, as can be seen in Table 3. Concluding and revisiting the second hypothesis, which stated that music featuring more artists increases overall interest in a song, the results seem to support this hypothesis. Music featuring two artists, as compared to music featuring one artist, increases overall interest in a song and gets people to 'act' more often, regardless of a song's visual properties. Whether this conclusion and the hypothesis holds when looking at more than two artists could be revealed by a follow-up study.

The third effect that was studied is visualisation. This is, as shown in Table 4 and supported by the likelihood-ratio test in Table 6 below, the most significant attribute that was studied in this thesis. Natural visualisation increases the chance of potential consumers 'acting', compared to artificial visualisation. From the pre-test in section 8.2, this effect was expected, as Table C9 shows a structurally higher likability mean score for natural rated pictures, when compared to artificial rated pictures. When a consumer can choose between an option with a natural cover and an option with an artificial cover, when all other attributes remain equal, the chance of the consumer picking the natural cover is 66.54% (Table 3). These results support the third hypothesis, meaning natural visualisation of a cover attracts more potential music consumers than artificial visualisation does.

Table 6

Likelihood-ratio tests of the conjoint experiment.

Source	L-R ChiSquare	df	Prob > ChiSq
Colour	97.822	3	<.001
Visualisation	162.884	1	<.001
Number of Artists	66.219	1	<.001
Fitting or Non-fitting*Colour	98.835	3	<.001

Furthermore, there is a significant interaction effect between the cover colour and the title of a song. Table 4 shows that the interaction effect is significant. The likelihood-ratio test in Table 6 supports this finding. The parameter estimates of the different colours are clearly affected when the song titles are fitting, as can be seen in Table 7. In this table, the estimates of the colours yellow, red and green shift away from zero and become more negative when song titles are fitting, as compared to the situation where song titles are not fitting the cover colour, meaning the effect of colour becomes larger when there is song title-colour congruency. Only the colour green and its interaction effect with fitting song titles were statistically nonsignificant at an α = 0.01 level. As the estimates below represent utility values in effect coding, the estimates of the different levels of each attribute, including the 'level 1' of each attribute as shown in Table 1, must add up to zero (Osborne, 2015). This means the colour blue has an estimate of $0.184 + 0.426 + 0.019 \approx 0.629$.

Table 7

Parameter estimates of the conjoint experiment.

Term	Estimate	Std. Error	Lower 99%	Upper 99%
Colour [Yellow]	-0.183798599	0.0582131554	-0.33376	-0.03384
Colour [Red]	-0.426402360	0.0611895342	-0.58403	-0.26878
Colour [Green]	-0.019128104	0.0598913946	-0.17341	0.135152
Visualisation [Artificial]	-0.343674453	0.0279121128	-0.41558	-0.27177
Number of Artists [1]	-0.225593469	0.0283965086	-0.29874	-0.15244
Fitting or Non-Fitting*Colour [Yellow]	-0.249023444	0.0863089758	-0.47136	-0.02669
Fitting or Non-Fitting*Colour [Red]	-0.676193987	0.0982922564	-0.92939	-0.42299
Fitting or Non-Fitting*Colour [Green]	-0.063963632	0.0857150062	-0.28477	0.156838

Note: the inclusion of the three main effects and the interaction effect of the 'fitting' or 'non-fitting' song titles on colour generates a BIC of 3698.644, which is lower than when removing variables or adding any interaction effects for gender, age, or the respondents' preferred music distribution service. A lower BIC means a better prediction model. Through the 99% confidence intervals, it is clear that only the colour green and the moderator effect of the fitting song titles with the colour green are nonsignificant at an alpha level of 0.01, as these intervals include 0.

The finding of a significant interaction effect is supported by the probability profiler grid tables of Table C19 and Table C20. These tables are both constructed against the baseline of a blue cover colour, natural visualisation and two artists included in the presentation of a song. Table C19 shows the probability of taking certain options over the aforementioned baseline option, in a situation where song titles do not fit the colour of a song's cover. Table C20 shows the same, but then in an environment where all song titles fit the cover's colour. The fitting options show smaller chances of picking a cover with any of the other colours than blue, compared to the non-fitting options, indicating a bigger effect of colour when song titles are congruent with colour. The results of the conjoint experiment support the final hypothesis, which states that there is a significant positive interaction effect between song titles and the colour variable, making colour an even more important attribute when it is congruent with a song's title.

Interaction effects between the three main attributes and gender, age and respondents' preferred music distribution service (MDS) were checked for, but found nonsignificant. This means gender, as well as age and people's preferred MDS have no significant impact on the strenght or sign of any main effect.

Maximising desirability – 'desirability' meaning 'a desirable combination of properties' (Derringer and Suich, 1980) – in the utility profiler of SAS JMP, it shows the attribute-levels that, when combined, form the ideal choice option. As expected, this choice option consists of a blue colour, a natural visualisation type, includes two artists and the song title is congruent with the colour of the cover. This is shown in further detail in Figure C9 in Appendix C.

Returning to the statistical model that was first presented in section 8.3.1, the beta coefficients (estimates) of the model can be filled in using Table 7. The complete model is presented below, in Equation 3. This equation is in line with the utility profiler in SAS JMP. It shows once again that a blue, natural cover with two artists and a congruent song title gives the highest utility a consumer can experience in picking a song with the given attribute-levels.

$$\begin{gathered} U_i = 0 - 0.184 \times \text{Yellow}_i - 0.426 \times \text{Red}_i - 0.019 \times \text{Green}_i \\ -0.344 \times \text{Artificial}_i - 0.226 \times [1]\ \text{Artist}_i - 0.249 \times \text{Fitting}_i \times \text{Yellow}_i \\ -0.676 \times \text{Fitting}_i \times \text{Red}_i - 0.064 \times \text{Fitting}_i \times \text{Green}_i + \varepsilon_i \end{gathered} \quad (3)$$

Applying this equation to all possible combinations of attribute-levels yields utilities, as shown in Table 8 below. The table is sorted by utility, from lowest to highest. This means 1 is the least favourable option and 32 is the most favourable option.

Table 8

Utility profiler grid table for all studied choice options (sorted by utility, from lowest to highest).

Option	Color	Visualisation	Number of artists	Fitting or non-fitting	Utility (U_i)
1	Red	Artificial	1	Fitting	-1.671864269
2	Red	Artificial	2	Fitting	-1.220677331
3	Yellow	Artificial	1	Fitting	-1.002089965
4	Red	Artificial	1	Non-fitting	-0.995670282
5	Red	Natural	1	Fitting	-0.984515362
6	Yellow	Artificial	1	Non-fitting	-0.753066521
7	Green	Artificial	1	Fitting	-0.652359658
8	Green	Artificial	1	Non-fitting	-0.588396026
9	Yellow	Artificial	2	Fitting	-0.550903027
10	Red	Artificial	2	Non-fitting	-0.544483345
11	Red	Natural	2	Fitting	-0.533328424
12	Yellow	Natural	1	Fitting	-0.314741058

Table 8 (continued)

Utility profiler grid table for all studied choice options (sorted by utility, from lowest to highest).

13	Red	Natural	1	Non-fitting	-0.308321375
14	Yellow	Artificial	2	Non-fitting	-0.301879584
15	Green	Artificial	2	Fitting	-0.201172721
16	Green	Artificial	2	Non-fitting	-0.137209089
17	Yellow	Natural	1	Non-fitting	-0.065717614
18	Green	Natural	1	Fitting	0.034989249
19	Blue	Artificial	1	Non-fitting	0.060061141
20	Green	Natural	1	Non-fitting	0.098952881
21	Yellow	Natural	2	Fitting	0.13644588
22	Red	Natural	2	Non-fitting	0.142865562
23	Yellow	Natural	2	Non-fitting	0.385469323
24	Green	Natural	2	Fitting	0.486176186
25	Blue	Artificial	2	Non-fitting	0.511248078
26	Green	Natural	2	Non-fitting	0.550139818
27	Blue	Natural	1	Non-fitting	0.747410047
28	Blue	Artificial	1	Fitting	1.049242203
29	Blue	Natural	2	Non-fitting	1.198596985
30	Blue	Artificial	2	Fitting	1.50042914
31	Blue	Natural	1	Fitting	1.73659111
32	Blue	Natural	2	Fitting	2.187778047

Equation 4 gives the probability that a consumer clicks option i over all other options j to n.

$$\text{Likeliness to act}_i = \frac{e^{U_i}}{e^{U_i} + \sum_j^n (e^{U_j})} \tag{4}$$

Where i is the option from which the likeliness to act is being calculated, against n other options, starting with option j. As an example, the likeliness of a consumer to click option 1 over option 2 and 3 in Table 8 is (Equation 5):

$$\text{Likeliness to act}_1 = \frac{e^{-1.672}}{e^{-1.672} + e^{-1.221} + e^{-1.002}} \approx 0.221 \tag{5}$$

Meaning the chance of a consumer picking a red, artificial visualised cover with one artist and a fitting song title, over options 2 and 3 in Table 8 is about 22.1%. Likewise, comparing the likeliness of a consumer to pick the most favourable option over the least favourable option is 97.9%. Thus, each of the attributes potentially has a major effect on the consumer choosing to click one song over another, solely based on its cover's visual and linguistic characteristics.

In short, a blue and natural cover typically does the best job in drawing attention from potential listeners, when compared to the other attribute-levels for colour and visualisation that were studied. In addition, a colour-fitting song title enlarges the positive or negative effect a certain colour has on consumers' likeliness to 'act'. Moreover, having two artists collaborate on a song usually draws more consumer attention as opposed to a solo song, even in situations where the artist(s) involved are unknown.

10 VISUAL MARKETING PLAN

Considering both the qualitative, as well as the quantitative aspect of this thesis, a visual marketing plan is drawn up, following the seven P's theory by Booms and Bitner (1981) and the five 'competitive forces' by Porter (1980). The main aim of this visual marketing plan is to tackle the problem that Idir Makhlaf and Thom Jongkind pointed out in Appendix B: making sure of visual marketing consistency, without sacrificing creativity and becoming boring.

In the seven P's theory of Booms and Bitner (1981), they introduce 'process', 'participants' and 'physical evidence' to the four P's theory by McCarthy (1960), in order to make it more relevant for service firms. The traditional four P's stand for 'product', 'price', 'place' and 'promotion'. Realising what these seven P's of songs or albums in the modern music industry mean, can help artists or record labels to gain an understanding of what a song can offer to potential consumers.

Applying this theory by Booms and Bitner (1981) to a visual marketing plan, it quickly becomes clear that 'promotion' is the most important component for the purpose of musicians or record labels wanting to sell or promote their music via streaming services. The other components, in this case mainly the 'process' component, serve as support. 'Product', 'price', 'participants' and 'physical evidence' only have a potential minor impact on whether or not a consumer takes the first step of clicking a song – that they don't know in any way – on Spotify, YouTube, or other music streaming platforms. The 'place' or region where the song will be listened to is fixed: online, wherever the respective streaming platform is accessible. On top of the song's visual characteristics on streaming platforms, the song can also be promoted via social media channels. Paid advertisements around the moment the song is released can provide an effective solution. However, as Marc Bandecchi mentioned (Appendix A), paid advertisements can negatively affect the customer's perception of the artist or record label and thus have to be handled with care. This is where the 'process' component supports the 'promotion' component of the marketing mix, to make the consumer's experience as smooth as possible (Booms & Bitner, 1981). Monitoring and nurturing customer experiences while advertising music (paid or unpaid) is a tough challenge.

Knowing what a song can potentially offer music consumers, a visual marketing strategy can now be developed to stand out as much as possible on these points in the competitive environment of the modern music industry. In Porter's paper 'How competitive forces shape strategy', he states five forces that have an impact on business strategies in a competitive environment (Porter, 1980). To a certain extent, an artist can be seen as a 'business', while a record label, of course, is a business in a very competitive environment. For that reason, some of the forces can be applied to musicians, as well as record labels in the modern music industry where platforms like Spotify play a key role. Of the five forces, the 'rivalry amongst existing competitors' is impacted by the other four forces, which are the 'thread of new entrants', the 'bargaining power of suppliers', the 'threat of substitute products' and the 'bargaining power of buyers'. Hence, first the other four forces are discussed in a visual music marketing environment, after which the rivalry of existing competitors is discussed.

Starting with the threat of new entrants, this is a big threat in the modern music industry. As the qualitative interviews (chapter 5) pointed out, the music industry is fast-paced. The barriers for new artists to enter the market are low, while switching costs for consumers are non-existent. There is brand loyalty in the form of fan bases of existing artists or record labels, but this fan base can only be established when the music of an artist of band is first clicked and listened to. Visually convincing the consumer to click on songs is already done at an earlier stage in the process.

Moving on with the bargaining power of suppliers, this force is relatively small, as the number of 'suppliers' is very large. Besides, all of the songs have similar visual format in the current most-used music streaming platforms: Spotify has covers like the ones in Figure 1 and YouTube has thumbnails for all music videos. For that reason, the uniqueness of each song only extends to a certain point.

The threat of substitutes is large. Music consumers have a tendency to substitute and switching costs are non-existent. On top of that, there is a big number of substitutes (other songs) on the different music distribution platforms. The fact that a song on Spotify is skipped within the first 30 seconds for about 35% of the time supports this, as it shows that consumers are able to switch quick, with lots of substitutes to choose from (Lamere, 2014).

The bargaining power of buyers, or in this case music consumers, is very large. Again, the non-existent switching costs, together with the big number of consumers and the ability to substitute easily, ensures that the consumer is in control of the music streaming business.

The aforementioned forces all jointly create a great rivalry amongst existing competitors. There is a big number of competitors, with lots of diversity in musical offer. For that reason, it seems even more important for artists and record labels to catch consumer's eyes and increase or even maximise their likeliness to 'act' on songs.

The small bargaining power of musicians and record labels in combination with the great bargaining power of the consumer shows, once again, that the consumer determines the music industry. Properly studying consumer behaviour, as has been done in the quantitative part of this thesis, can therefore be of great strength for artists and record labels.

In short, the conjoint experiment can act as a handbook for the 'promotion' part of the marketing mix. Blue generally does best, but it can be alternated with other colours, colour tones and colour combinations, while keeping the other attributes at high desirability levels, in order to visually release varied and creative visual content as a musician or record label. Similarly, other attributes can be alternated, while the rest of the visual characteristics of a song are kept equal, making sure utility levels are as high as possible.

While visual marketing seems very important in the modern music industry, there are of course other forces like the quality differences between songs and the word of mouth marketing of other consumers that make up a big part of the likeliness of a consumer to click on certain songs. This thesis has also brought other – non-visual – factors to light that potentially have an influence on whether or not to stand out as an artist or record label. These factors and their implications will shortly be reiterated in section 11.1.

11 CONCLUSION

In the final chapter of this thesis, three separate sections discuss the overall findings, as well as the implications these have for managers and academia. Also, recommendations for future research are made. Returning to both the qualitative and quantitative aspects of this research, it is discussed where this thesis fits into the existing literature. In section 11.1, all sub-questions are answered shortly, in order to form an answer to the research question of this thesis: 'to what extent do visual features and the number of artists per song in the modern music industry impact consumer interest and/or consumer buying behaviour?'

11.1 DISCUSSING OVERALL FINDINGS

The interviews with Marc Bandecchi (Appendix A) and Idir Makhlaf and Thom Jongkind (Appendix B) are unanimous when it comes to the most important streaming platforms of the current music industry. According to the interviewees, Spotify leads the music streaming generation and YouTube follows closely. However, the interviews are not unanimous when it comes to the best way to visually stand out from the crowd as an artists or record label, implying that there are multiple ways to visually stand out and get your message across in the modern music industry. Findings of the conjoint experiment done in this thesis support this, as all studied attributes have a very significant impact on the likeliness of a consumer to 'act'. It was shown that a blue coloured, naturally visualised cover and a song title that is perceived to be congruent with the cover colour, gives the highest likeliness for a consumer to become interested in a song and act accordingly. Furthermore, findings suggest that the so-called 'featuring phenomenon' exists, regardless of the visual properties of a song. Of the studied attributes, colour has the biggest effect on a consumer's likeliness to 'act'. Visualisation type is the most significant attribute among all, when the moderator effect of song titles on colour is included in the regression equation. When only taking main effects into account, colour is the most significant attribute.

Concluding, visual features and the number of artists per song can have a big impact on consumer interest or buying behaviour towards a song. In the modern music industry, other factors like consistency and congruency in social media use play a role too, but they have a more significant role when a consumer is already a fan and/or follower of your social media channels. In a consumer's decision to take the first step in potentially becoming a fan – by clicking a song of an artist or record label for the first time – visual characteristics of the song are key. Different attribute-levels can lead to one song being visually preferred over another with a probability of up to 97.9%. Visual characteristics of a song therefore are the first determinant to whether or not a musician even gets a chance to let the music convince someone in becoming a long-lasting fan of his or hers.

11.2 IMPLICATIONS FOR MANAGERS AND ACADEMIA

For managers, especially marketing managers of record labels and artists, the findings of this thesis can improve a record label's or artist's recognisability and make them stand out. Introducing a combination of a blue, natural cover photo and releasing songs with multiple (other) artists could significantly increase the visual appeal of a song to potential music consumers, likely resulting in more listeners and sales. Being an artist or record label, making sure the title of a song fits its cover colour could impact the likeliness of a consumer to click the song, too. It is, however, not a necessity and might even be counterproductive to give the same look to all upcoming covers of an artist's or label's songs. Being creative with colours, while keeping other variables like the natural cover picture in mind, or the other way around – using a blue but artificial cover graphic – would not compromise the desired results too much. In the end, posting consistent, but varied content on all social media channels of an artist or record label is the key to maintain and expand your current fan base, according to established artists and label managers. But in order to get the attention of a potential fan base at all, the music must first stand out visually.

For academia, this thesis would have its own space within existing literature. There have been multiple previous studies on audiovisual congruency in advertisements and the effect of audio on visuals. Examples of studies in that scope are the ones by Lalwani et al. (2009) and Rosenfeld and Steffens (2019), that were mentioned in chapter 4 of this thesis. But, almost no research has been conducted the other way around: the effect of visual characteristics on audio. This thesis changed that and studied the effect of visual characteristics on the likeliness for a consumer to click a song. Considering the study by Holt (2011), who found that the distribution and communication about music has become more visual, the scientific importance of this thesis simultaneously increased.

11.3 LIMITATIONS AND FUTURE RESEARCH RECOMMENDATIONS

In this thesis, a few limitations that form a source for future research have come to light. First of all, there are some limitations to the data of the quantitative research part of the thesis. In terms of age of the respondents, the data is right skewed, meaning there have been a lot more younger than older respondents to the conjoint experiment. This makes that the findings of this experiment are not directly generalisable to all age groups. It might be debatable whether this is a limitation of this research, as it is mainly the younger generation that uses Spotify or other visual-based music distribution platforms, while middle-aged and elderly people are more likely to listen to music on the radio or buy CDs (Feldman & Weir, 2018; Pedrero-Esteban et al., 2019). Nevertheless, this remains an interesting source for future research: how would you, as a musician, record label or even radio station, (visually or not) convince the older listener to listen to your music, without losing the younger generation entirely?

Another potential limitation of this thesis of the same draw could be that the research is Spotify focused. The environment of the conjoint experiment, as shown in Figure 3, is imitated from original Spotify covers, including a Spotify background. Also, over half of the respondents of this experiment has Spotify as their preferred music distribution service (MDS). Even though it is likely that the results of this thesis are generalisable across other platforms, as the introduction of the preferred MDS of respondents to the statistical model did not result in a significant interaction effect between it and any of the main effects, it would still be better to conduct a follow-up study to be sure. After all, all of the music distribution platforms that were mentioned in this thesis play an important role in the modern artist's or record label's total revenue and recognisability.

Within the design of the conjoint experiment itself, there are also a few limitations that will be mentioned briefly. First, there is the fact that the covers used in the conjoint experiment all consist of a single colour, whilst a combination of colours might result in even better results. As White et al. (2021) suggested, a blue-green analogous colour set elicits a high level of purchase intention. Another colour-related limitation is in the fact that only four different colour tones (Figure 1) are used, while in reality, there are many different tones of blue, green, yellow and red. A more extensive follow-up study could show whether colour combinations and/or the use of other colours and colour tones lead to different results

Continuing on the limitations of the conjoint experiment, as briefly mentioned in chapter 9, the 'number of artists' attribute only had two options, which seems sufficient, as usually there are no more than two artists or bands working together on a single song. However, results now imply that more artists or bands is simply better, when it comes to the marketing of music, while it makes more sense to assume a non-linear function and a certain 'limit', where the addition of another artist does not increase a consumer's likeliness to 'act'. A follow-up study could investigate what this function could look like.

Lastly, visual marketing in general has the limitation that not all topics can be generalised all over the world, due to cultural differences. This thesis mainly focused on Western European respondents, as the conjoint experiment was distributed in that region. As De Mooij and Hofstede (2011) state, 'most aspects of consumer behaviour are culture-bond'. This also applies to visual marketing in the music industry. Taylor et al. (2013) stated that colour preferences are not universal, which might have a big impact on how the results of this thesis may differ across different countries and regions. For the same reason, a customised international marketing strategy is recommended by Madden et al. (2000) if the meaning associated with a colour differs across cultures. The study by Madden et al. (2000) supports the finding of this thesis that blue is a very likable colour across eight different countries, while with some other colours, big and significant likability-differences across regions can be noticed. A recommendation for future research would be to study the impact and sign of the different attribute-levels used in this thesis – especially for the colour attribute – on the likeliness to act, across multiple different cultures.

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APPENDIX A: INTERVIEW MARC BANDECCHI (ARCANDO)

Q1 What do you see as the most difficult part in the modern music world? And how do you deal with that?

A1 *ARCANDO: Collaborating with other artists is the hardest part. Sometimes you expect other artists, record labels or other agencies to be professional, but most of the time they are way less professional than they seem to be.*

Q2 Who do you think is the best artist you've ever worked with, purely in terms of music production and music quality? And why?

A2 *ARCANDO: Actually, these are my friends ThatBehavior and Oddcube. This might sound weird, but we are always on the same page and I learned a lot from these guys, even though they are not that famous and they probably never will be, because of their inconsistent social media appearances.*

Q3 The modern music industry has changed a lot from a few years ago: streaming services, for example, have become very large. Looking purely at your area (EDM), what do you think are the most important music labels and streaming platforms of the moment?

A3 *ARCANDO: In terms of music labels, this is very subjective. It differs a lot per genre. For EDM, Spinnin' Records and Revealed Recordings usually do best, though. As for streaming platforms, Spotify does best at this time. But there are also small underground streaming platforms like Audiomack that are building their way up.*

Q4 As a follow-up to the previous question: what do you think these successful platforms have tackled better than platforms that have become smaller in recent years, such as Soundcloud, for example?

A4 *ARCANDO: Soundcloud was very popular, but they didn't evolve over time. They stayed the same and never updated their site. Also, Soundcloud has this 'repost' option that gives you the opportunity to add the tracks of others to your timeline. When artists do that, their fans will get 'stalked' with tracks from people they don't follow, which is annoying. The platform has become very messy, while Spotify is simple and back to basic and every fan gets what they actually sign up for. Also, the audio quality on Soundcloud is very poor, compared to other platforms like Soundcloud, Audiomack and even YouTube. In short, Soundcloud had a leading position, but they lost it because they didn't adapt over time* *and the changes they did made it worse, rather than better. Others stayed simple and improved in the very basics, like audio quality.*

Q5 As you know, my research is mainly about visual properties of music. Think of album covers or covers of individual songs, for example. Do you personally make decisions about the songs to be released on music labels when it comes to visualizing them? For example, do you have any influence on the cover artwork of your own song, when releasing it at a label? And do you decide about the track's name yourself?

A5 *ARCANDO: The name of the track is solely decided by the artist, always and without exception. If not, it would feel as if the hospital would decide about the name of your baby; that doesn't make sense at all. In terms of artworks, some labels are very strict and want their own artworks for the track. But as I am personally convinced that it is my track, and not the label's track, I don't work like that anymore, now that I have the leverage to demand stuff because of my relatively big fan base. I want my tracks, as well as the artworks, to have my own vibe and I won't change this for a label. If they don't want me to decide about it myself, that is ok, but then I simply don't work with them anymore and release my music somewhere else. But for starters, covers and other visual elements are usually decided by labels and not by the artist.*

Q6 Imagine for a moment that you are going to release a new original, without input from another artist. Just, a big Arcando-only track. You are going to make choices about the name of the song and the cover that attracts the most attention from people who do not yet have you in their regular playlist. So you mainly want to attract <u>new people</u>. For the sake of simplicity, leave your current fans out of the equation. Which of the following visual elements do you think has the most impact to attract new people and why?

- Colours used in e.g. the cover of the track.
- Name of the track.
- The background of the cover: e.g. simplistic / with people on the cover / something abstract.
- Natural visualisation (like a picture) versus artificial visualisation (made with a computer).
- How well the track name and cover match: e.g. obscure name + obscure image in a dark colour on the cover, versus a combination that is less congruent.
- Something completely different: explain.

A6 *ARCANDO: If you want to attract new fans, the cover has to stand out. For that reason, I would use bright colours and a remarkable background. I think these elements are most important. But, when creating a cover, the artist or cover-designer should never forget about the consistency of the artist. The covers should fit and be comparable to covers that the artist has used before. That way, an artist can create his own 'brand', which is important for the future of his/her name. I think it is also important to have a coherent whole.*

Q7 If you focus on your existing fan base, rather than potential listeners who don't know you yet. Would the answer to the previous question be different then? Why? [Explanation: So I'm basically asking here to what extent you think your current fan base, i.e. the people you've already reached, are different from the potential listeners you still want to reach]

A7 *ARCANDO: No, I would not do this any different than trying to find new consumers. In the end, you want to build on a long term relationship with your fans, so they have to like your music as well as your visual presentation from the start. Also, I think colours and background items always are the most important in terms of the visual representation of music. By the way, I don't think track names are important at all, as I don't think people will decide not to click on a track just because of the title of a track. The visuals are a lot more important as far as I know.*

Q8 Even though you think track names don't have a big impact, you also stated that you value consistency quite a lot and this also comes from track names I suppose. For that reason, I have the next question. What type of track name you think does best with calmer music genres like pop and jazz? And Why?

- Calm.
- Dark.
- Vivid.
- Romantic.

A8 *ARCANDO: I think track names are really made up per individual track and are not genre specific. But, typically with slower music you tend to find calmer track names. But calm track names can still be dark or calm and emotional. However, they tend not to be vivid, as far as I am concerned. But as I am not working in the pop or jazz scene, I cannot say for sure.*

Q9 What type of track name you think does best with more energetic electronic genres like progressive house or even hardstyle? And Why?

- Calm.
- Dark.
- Vivid.
- Romantic.

A9 *ARCANDO: These tend to be more vivid. But they still can be dark or romantic of course. I think in general for faster paced songs, the song titles are more vivid, in combination with some darkness or a touch of emotion. For slower paced tracks, they are more calm with a little bit of emotion or darkness. But keep in mind, lots of tracks have singers or singer-songwriters and when they come up with a good song text, most of the time the song will be named after it.*

Q10 Have you (or an external company / your marketing manager, if any) ever done specific customer research into your own fan base, visually? For example, do you know specifically what your current fan base wants to see in video clips and how you (besides releasing the best possible music of course) get them to be the most visually satisfied?

A10 *ARCANDO: I have never had a marketing manager or external company research this. That is why I find it very interesting that you will do some research in that area. I always try to stay consistent in all parts of my marketing: posting content consistently on social media, being consistent in music quality and creativity, having the covers of my tracks in the same – recognisable – style. But I am curious what you will find out about this in your study.*

Q11 You are quite active on social media. Do you also try to attract new listeners via social media channels such as Instagram, for example via Instagram advertisements or posts that you hope will go viral? Or is social media a way for you to maintain the current fan base and build a long-term relationship?

A11 *ARCANDO: I did an advertisement on TikTok once. Although it gained me a lot of listeners, it also gained me a lot of hate, as there is about no one in the world who likes unsolicited advertising. I would never do that again, as I value the quality of my fan base way more than the quantity of my fan base. On my personal Instagram account for example, I do post about twice a month and I post stories every day. I think the key word in all of my personal marketing is 'consistency'.*

Q12 Earlier in this interview you answered the question who the best artist is you have ever worked with. There's a good chance that this artist isn't the most famous artist you've ever worked with. How do you think it is that – in many cases – the best artist when it comes to music quality or creativity is not always the best known artist? To what extent do you think this has to do with marketing: promoting the artist, especially visually?

A12 *ARCANDO: Although I value these guys the most, ThatBehavior and Oddcube are definitely not the most famous artists I worked with, indeed. I think Josh A is the most famous one. He has about 4 million monthly listeners on Spotify. The reason why he is so famous has to do with his marketing, surely. He has his own unique style, both in music terms as well as in visual terms. His covers, for example, are very unique and recognisable. I am sure that does help him to be more famous. Next to that, he is very consistent over all of the platforms he is active on. On YouTube, he has over a million subscribers and on Instagram he has over 100.000 followers. He is good and consistent on all platforms, which creates a lot of awareness for him.*

Q13 Going deeper into the previous question, do you think there are a lot of talented artists who end up not making it because their visual marketing strategy isn't good enough?

A13 *ARCANDO: Yes, of course. There is so much talent out there that does not get recognised enough. You are one of the many examples yourself. You have had your highlights, but never got recognised on the big stage yet.*

Q14 When I compare you to other artists that are bigger on social media, you do relatively very good on Spotify. You got around a million monthly listeners on the Spotify platform. What is the reason for this? Does it have to do with your visual marketing strategy? Or do you think it is mainly because of the fact that you make a lot of remixes of famous tracks, that gives you more exposure because people who search for the original tend to be interested in remixes of the original too?

A14 *ARCANDO: It is a combination of both. It does indeed help a lot to make remixes of famous tracks. But also, the consistency that I have on my social media, I have in an even more extreme way on Spotify. The covers fit each other, sometimes one cover even complements the other, to tell a chronological story. Also, I try to upload new content at least once a month to make sure my followers and fans are treated well.*

Q15 Thank you for your time, of course. Do you still have any specific visual marketing-related question that you would like to see answered in my research?

A15 *ARCANDO: I have done music school at the Herman Brood Academy. Although I learned some interesting things there, I will leave the research to you. I am sure you can find the marketing-related answers that most artists are looking for!*

Closing [short version]: Thanks again for your time, Marc. We will talk soon!

APPENDIX B: INTERVIEW IDIR MAKHLAF & THOM JONGKIND (BLASTERJAXX)

Q1 With ‘big room house’, you two almost single-handedly designed a new genre. In addition, for a few years now you have been label managers of Maxximize Records, a label affiliated with a major player in the market: Spinnin' Records. How do you like that? And how intensive is it to be both Blasterjaxx and label manager?

A1 *BLASTERJAXX: We are not just with the two of us when it comes to the label. When releasing a track on Maxximize Records, usually a team of about seven or eight people make it to a success. As long as you keep your health in mind and take enough breaks, everything we do right now is very doable.*

Q2 Who do you think is the best artist you've ever worked with, purely in terms of music production and music quality? And why?

A2 *BLASTERJAXX***:** *That have to be W&W and D-Block and S-te-fan. First of all, we like working with duos, as we are a duo ourselves and it just fits better. But these guys are very good. When we sit down in the studio, something beautiful always comes out. These are about the only two acts that are on the same level as the two of us are, when it comes to production talent.*

Q3 Question for Idir: It is known that you stopped doing most of the tours / gigs abroad a few years ago. You regularly hear about artists who cannot or do not like the extensive travel etc. Do you think this is the most difficult part of today's global music industry? The fact that you are expected by fans on every continent every year for shows?

A3 *IDIR [BLASTERJAXX]: Some people can handle it just fine, but I'm just not cut out for it. Traveling a lot was fun the first year, because everything is new. But then it just got too much for me. It made me unhappy. I think we have the perfect blend now that Thom does the traveling and gigs; he really puts up a show. And I make the music and have the most fun here, in the studio and also with the management of Blasterjaxx.*

Q4 Question for Thom: what do you see as the most difficult part in the modern music industry? And how do you deal with that?

A4 *THOM [BLASTERJAXX]: First of all, it is not as if I think traveling the world is easy, or as if I never want a break, because I definitely do want a break sometimes. But for me,* *the hardest part in the current music industry consists of the things you have no control over. Like politics during the pandemic, for example.*

Q5 The modern music industry has changed a lot from a few years ago: streaming services, for example, have become very big players. Looking purely at your area (EDM), what do you think are the most important music labels and streaming platforms of the moment?

A5 *BLASTERJAXX: When it comes to labels, it's different per artist. For us, Maxximize Records is most important of course. But we also value Revealed Recordings and Warner Music a lot. On the other hand, for streaming platforms, Spotify and YouTube are very important, but also Deezer is a big upcoming player, especially in France. A little while ago, we were surprised to see that our fan base is so big on this platform. And it keeps growing.*

Q6 As a follow-up to the previous question: what do you think these successful platforms have tackled better than platforms that have become smaller in recent years, such as Soundcloud, for example?

A6 *BLASTERJAXX: Some platforms just evolved, while Soundcloud stayed itself. Soundcloud is good for artists to show themselves to labels, etc. But it's not a high quality platform anymore, as the audio quality is not that high and they never really improved over the last years.*

Q7 As you know, my research is mainly about visual properties of music. Think of album covers or covers of individual songs, but also titles of tracks. Do you personally make decisions about the songs to be released on your label when it comes to visualizing them? For example, do you influence track names of other artists or colours on the cover that is made for songs?

A7 *BLASTERJAXX: Well, it has to fit the label. But the track name, we don't influence at all. We do want the audio to fit the track name as well as the cover, but the cover needs some sort of consistency, so that everyone sees it is a Maxximize Records track. Usually, we work with the artist of the track and overthink the cover together.*

Q8 Imagine for a moment that you are going to release a new original, without input from another artist. Just, a big Blasterjaxx-only track. You are going to make choices about the name of the song and the cover that attracts the most attention from people who do not yet have you in their regular playlist. So you mainly want to attract new people. For the sake of simplicity, leave your current fans out of the equation. Which of the following visual elements do you think has the most impact to attract new people and why?

- Colours used in e.g. the cover of the track.
- Name of the track.
- The background of the cover: e.g. simplistic / with people on the cover / something abstract.
- Natural visualisation (like a picture) versus artificial visualisation (made with a computer).
- How well the track name and cover match: e.g. obscure name + obscure image in a dark colour on the cover, versus a combination that is less congruent.
- Something completely different: explain.

A8 *IDIR [BLASTERJAXX]: I feel like the theme has a lot of influence. What we usually try is to make a track that fits an actual theme, like a Christmas themed track during Christmas holidays. We also made a track called 'Narcos' that was releasing at the same time that the movie Narcos came out. Coming back to your question, I think it's the congruent combination of the team that has most impact, in combination with the theme of the track, that must fit current affairs when it comes to attracting new listeners.*

THOM [BLASTERJAXX]: I feel like the consistency of the label or the collaboration with and fame of other artists will attract new listeners, rather than something visual. But when I really have to pick one out of these, I would go with the name of a track. I think that has some sort of influence, but like Idir said, it has to fit the track, as well as the cover of the track. By the way, we feel like working on tracks with other well-known artists definitely boosts consumer interest in this particular track. That's why we almost only work on collaborations since a few years.

Q9 If you focus on your existing fan base, rather than potential listeners who don't know you yet. Would the answer to the previous question be different then? Why? [Explanation: So I'm basically asking here to what extent you think your current fan base, i.e. the people you've already reached, are different from the potential listeners you still want to reach]

A9 *BLASTERJAXX: We don't think it would change our answer to the previous question. You keep your current fan base in mind, of course, but in the end, music is all about creativity and we make the track and all of its attributes how we like it, without too many constraints. Sometimes it works and sometimes it does not work so well. But we always* *assess the performance of the track and the marketing we have done for the track afterwards. And of course, there has to be some congruency: the visuals have to fit the audio and the song title.*

Q10 What type of track name do you think works best with quieter genres like pop and jazz? And why?
- Calm.
- Dark.
- Vivid.
- Romantic.

A10 *BLASTERJAXX: I think it's more common for quieter genres to use calm and romantic track names. But it is not a restriction of course. I mean we have had tracks of all sorts and also track names of all sorts. As a musician, you should not put these kinds of boundaries on the track name or on the track itself, for the sake of creativity.*

Q11 What type of track name you think does best with more energetic electronic genres like progressive house, big room house or even hardstyle? And Why?
- Calm.
- Dark.
- Vivid.
- Romantic.

A11 *IDIR [BLASTERJAXX]: I want to add one: 'euphoric'. It's close to vivid, but I always use 'euphoric' to describe our music to someone who doesn't know us yet. I think euphoric is the right word, but to a certain extent this is 'vivid'.*

THOM [BLASTERJAXX]: My answer would be the same as with previous question. There are no regulations that a genre is associated with certain track names. Usually, however, the more energetic a track is, the more energetic a track name will be. That makes sense. Also, don't forget that most track names come from vocalists that made a good vocal for the track. It has to fit the track.

Q12 Have you (or an external company / your marketing manager, if any) ever done specific customer research into your own fan base, visually? For example, do you know specifically what your current fan base wants to see in video clips and how you (besides releasing the best possible music of course) get them to be the most visually satisfied?

A12 *BLASTERJAXX: We didn't have a marketeer do this, on purpose, as we think it is bad for our creativity. For example, if we hear from the customer research that our fans like red colours, fire and a dark track name, it narrows down our creativity. Also, we cannot make a copy of an artwork for every new track we make. That would be boring.*

Q13 You are quite active on social media. For examples, you guys are posting a lot in your Instagram stories. Do you also try to attract new listeners via social media channels such as Instagram, for example via Instagram advertisements or posts that you hope will go viral? Or is social media a way to maintain the current fan base and build a long-term relationship? If you do, do you also get negative comments about it?

A13 *BLASTERJAXX: We do Instagram advertisements when we release new tracks. It makes our numbers go up, and that's what we want. Of course, we get negative comments about it, but everyone does it anyways. In the end, it is all about showing your face and your music to the world, in order to gain new fans and get recognised.*

Q14 Earlier in this interview you answered the question who the best artist is you have ever worked with. There's a good chance that this artist isn't <u>the most famous</u> artist you guys have ever worked with. How do you think it is that – in many cases – the best artist when it comes to music quality or creativity is not always the best known artist? To what extent do you think this has to do with marketing: promoting the artist, especially visually?

A14 *BLASTERJAXX: That's all about marketing. You are right, D-Block and S-te-fan are definitely not the most famous artists, but they don't have the best marketing either. We're not saying that you can buy yourself in. There's plenty of rich people who are just not good enough. But it is a combination of music quality, marketing and definitely luck to get there. We have had luck that we were such a hype in the 2013 – 2015 period. We are still living on that hype. But the marketing of our team made us grow further, along with the music we make and our gigs of course.*

Q15 Going deeper into the previous question, do you think there are a lot of talented artists who end up not making it because their visual marketing strategy isn't good enough?

A15 *BLASTERJAXX: Definitely. As we said, it is not as if marketing or money is everything. But you need it to get a chance. And then you need music quality and luck. Many potentially famous artists are already stranded at the first point of getting their marketing on point.*

Q16 The study will take about six months in total and will therefore be quite extensive. My final question is what exactly do you expect to get out of my research. Are there specific things about which you wonder from a marketing point of view whether you are doing it right? Then I can take that into account in my research.

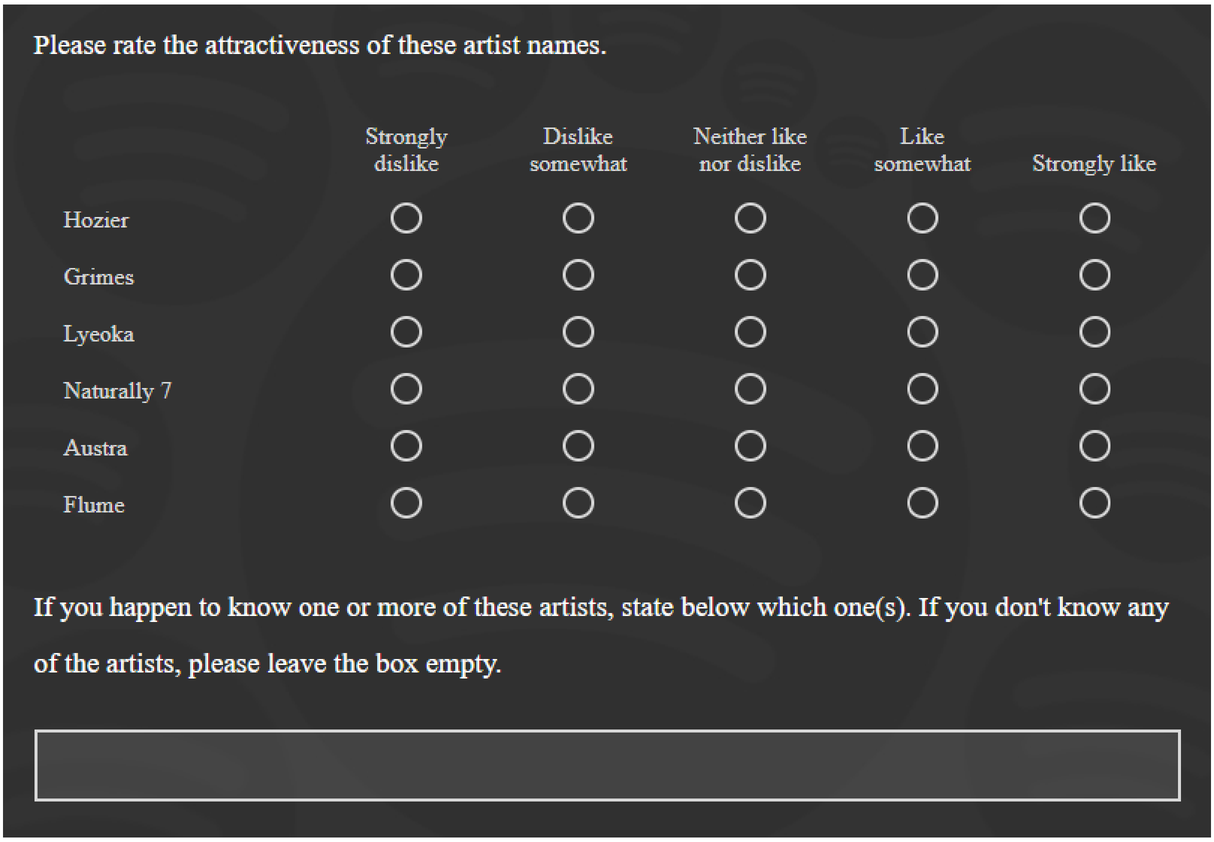
A16 *BLASTERJAXX: We just wanted to help you and are curious what you will learn from the research. We will leave it up to you to think of what is important to know and what is not important to know.*

Closing [short version]: Thank you guys for your time of course. We will talk soon!

APPENDIX C: PRE-TEST AND CONJOINT EXPERIMENT RESULTS

Figure C1

Artist-part of the pre-test.



Note: the answer to this question leads to scores (Strongly dislike = 1, Strongly like = 5).

Table C1

Descriptive statistics for the likability rating of each artist name.

	N	Mean	Std. Deviation	Std. Error Mean
Hozier	30	2.133	.7761	.1417
Grimes	30	2.200	.7144	.1304
Lyeoka	30	3.700	.9523	.1739
Naturally 7	30	3.833	.8339	.1523
Austra	30	3.900	.5477	.1000
Flume	30	3.867	.6288	.1148

Table C2

Descriptive statistics for the total average likability rating of all artist names combined.

	N	Mean	Std. Deviation	Std. Error Mean
Artist Score	180	3.27	1.082	.081

Table C3

One-way ANOVA to compare the means of artist-likability scores (all six artists).

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	110.761	5	22.152	38.974	<.001
Within Groups	98.900	174	.568		
Total	209.661	179			

*Note: the answer-scores of 30 respondents of this pre-test are analysed through SPSS, to see whether some artist names' likability scores deviate significantly from the rest. Only the answers of 30 respondents were taken into account for this analysist, as the other 6 respondents stated to know one of the artist names, possibly biasing their given scores. Going with an alpha of 0.01, the F-value of 38.974 is **higher** than the critical value of 3.21 (DF numerator = 5, DF denominator = 100).*

Table C4

One-way ANOVA to compare the means of artist-likability scores (artists minus Hozier).

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	64.067	4	16.017	28.519	<.001
Within Groups	81.433	145	.562		
Total	145.500	149			

*Note: the answer-scores of 30 respondents of this pre-test are analysed through SPSS, to see whether some artist names' likability scores deviate significantly from the rest. Only the answers of 30 respondents were taken into account for this analysist, as the other 6 respondents stated to know one of the artist names, possibly biasing their given scores. Going with an alpha of 0.01, the F-value of 28.519 is **higher** than the critical value of 3.51 (DF numerator = 4, DF denominator = 100).*

Table C5

One-way ANOVA to compare the means of artist-likability scores (artists minus Hozier and Grimes).

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	.692	3	.231	.401	.752
Within Groups	66.633	116	.574		
Total	67.325	119			

*Note: the answer-scores of 30 respondents of this pre-test are analysed through SPSS, to see whether some artist names' likability scores deviate significantly from the rest. Only the answers of 30 respondents were taken into account for this analysist, as the other 6 respondents stated to know one of the artist names, possibly biasing their given scores. Going with an alpha of 0.01, the F-value of 0.401 is **lower** than the critical value of 3.98 (DF numerator = 3, DF denominator = 100).*

Table C6

Bonferroni post-hoc test to check for mean differences in artist names (in the n = 30 sample).

(I) Sample	(J) Sample	Mean Difference (I-J)	Std. Error	Sig.	99% Confidence Interval Lower Bound	Upper Bound
Hozier	Grimes	-.067	.195	1.000	-.74	.61
	Lyeoka	-1.567*	.195	<.001	-2.24	-.89
	Naturally 7	-1.700*	.195	<.001	-2.37	-1.03
	Austra	-1.767*	.195	<.001	-2.44	-1.09
	Flume	-1.733*	.195	<.001	-2.41	-1.06
Grimes	Hozier	.067	.195	1.000	-.61	.74
	Lyeoka	-1.500*	.195	<.001	-2.17	-.83
	Naturally 7	-1.633*	.195	<.001	-2.31	-.96
	Austra	-1.700*	.195	<.001	-2.37	-1.03
	Flume	-1.667*	.195	<.001	-2.34	-.99
Lyeoka	Hozier	1.567*	.195	<.001	.89	2.24
	Grimes	1.500*	.195	<.001	.83	2.17
	Naturally 7	-.133	.195	1.000	-.81	.54
	Austra	-.200	.195	1.000	-.87	.47
	Flume	-.167	.195	1.000	-.84	.51
Naturally 7	Hozier	1.700*	.195	<.001	1.03	2.37
	Grimes	1.633*	.195	<.001	.96	2.31
	Lyeoka	.133	.195	1.000	-.54	.81
	Austra	-.067	.195	1.000	-.74	.61
	Flume	-.033	.195	1.000	-.71	.64
Austra	Hozier	1.767*	.195	<.001	1.09	2.44
	Grimes	1.700*	.195	<.001	1.03	2.37
	Lyeoka	.200	.195	1.000	-.47	.87
	Naturally 7	.067	.195	1.000	-.61	.74
	Flume	.033	.195	1.000	-.64	.71
Flume	Hozier	1.733*	.195	<.001	1.06	2.41
	Grimes	1.667*	.195	<.001	.99	2.34
	Lyeoka	.167	.195	1.000	-.51	.84
	Naturally 7	.033	.195	1.000	-.64	.71
	Austra	-.033	.195	1.000	-.71	.64

*Note: * = The mean difference is significant at the 0.01 level.*

Figure C2

Example question for pre-test respondents to rate the perceived naturalness and likability of an image.

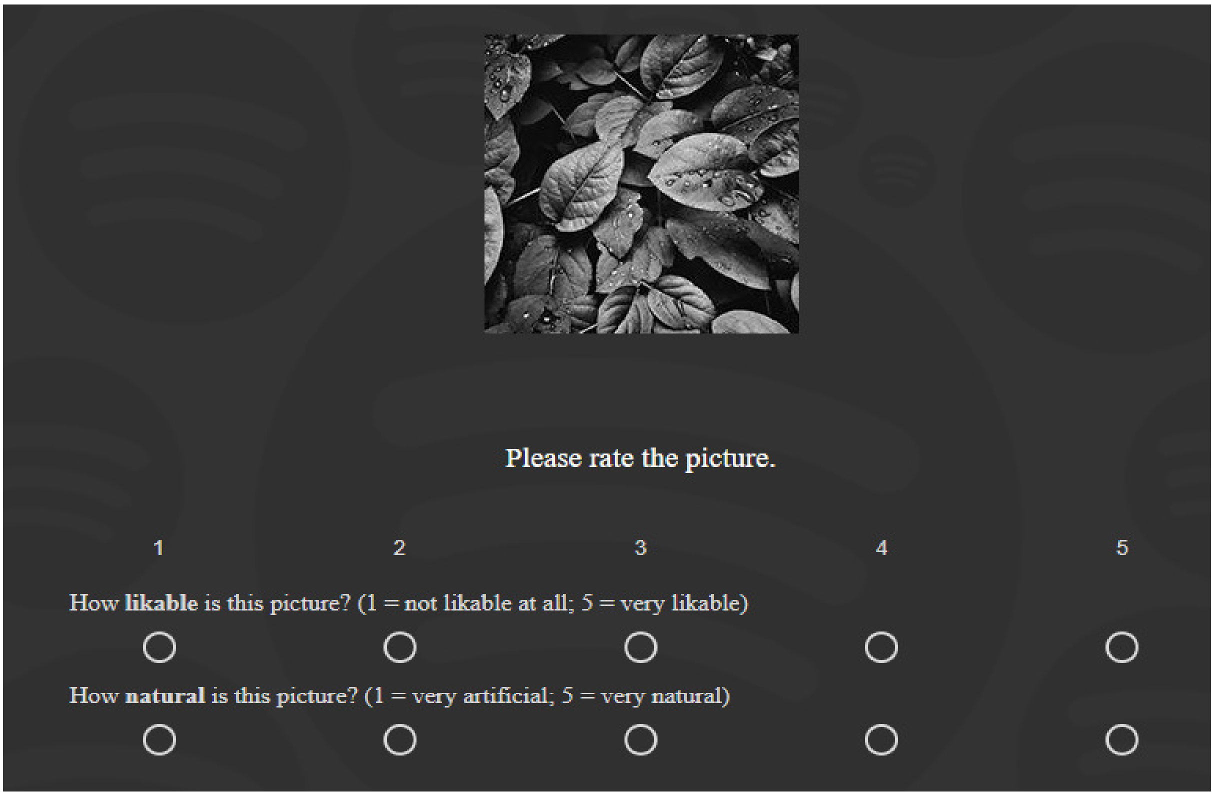


Table C7

One-sample t-test for every picture's natural versus artificial rating, compared to the scale mean of 3.

	t	df	Significance		Mean	95% CI of the Difference	
			One-Sided p	Two-Sided p	Difference	Lower	Upper
Naturalness 'A'	-22.007	35	<.001	<.001	-1.778	-1.94	-1.61
Naturalness 'B'	-16.372	35	<.001	<.001	-1.528	-1.72	-1.34
Naturalness 'C'	15.050	35	<.001	<.001	1.361	1.18	1.54
Naturalness 'D'	-18.708	35	<.001	<.001	-1.667	-1.85	-1.49
Naturalness 'E'	16.765	35	<.001	<.001	1.361	1.20	1.53
Naturalness 'F'	14.509	35	<.001	<.001	1.472	1.27	1.68
Naturalness 'G'	14.967	35	<.001	<.001	1.333	1.15	1.51
Naturalness 'H'	-14.936	35	<.001	<.001	-1.278	-1.45	-1.10
Naturalness 'I'	11.602	35	<.001	<.001	1.111	.92	1.31
Naturalness 'J'	-25.298	35	<.001	<.001	-1.778	-1.92	-1.64
Naturalness 'K'	-24.597	35	<.001	<.001	-1.833	-1.98	-1.68
Naturalness 'L'	17.602	35	<.001	<.001	1.611	1.43	1.80
Naturalness 'M'	11.481	35	<.001	<.001	1.194	.98	1.41
Naturalness 'N'	-20.131	35	<.001	<.001	-1.722	-1.90	-1.55

Note: the name of each picture in the first column of the table, corresponds with the picture as depicted in Table C8. Test value = 3.

Table C8

Every picture used in the pre-test, linked to the name (letter) of the picture, as given in Table C7.

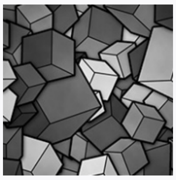
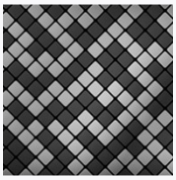
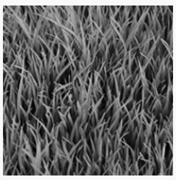
Letter	Picture	Perceived naturalness
A		The perceived naturalness of this picture is significantly **lower** than the scale mean of 3. This applies to both p-values of 0.1, 0.05 and 0.01. Indeed, the absolute value of the t-statistic of -22.007 is way higher than any of the critical values in the t-distribution table that apply to a sample with 35 degrees of freedom, while the mean difference is -1.778, and thus negative (Moore et al., 2016).
B		The perceived naturalness of this picture is significantly **lower** than the scale mean of 3. This applies to both p-values of 0.1, 0.05 and 0.01.
C		The perceived naturalness of this picture is significantly **higher** than the scale mean of 3. This applies to both p-values of 0.1, 0.05 and 0.01. Indeed, the t-statistic of 15.050 is way higher than any of the critical values in the t-distribution table that apply to a sample with 35 degrees of freedom, while the mean difference is 1.361, and thus positive (Moore et al., 2016).
D		The perceived naturalness of this picture is significantly **lower** than the scale mean of 3. This applies to both p-values of 0.1, 0.05 and 0.01.
E		The perceived naturalness of this picture is significantly **higher** than the scale mean of 3. This applies to both p-values of 0.1, 0.05 and 0.01.
F		The perceived naturalness of this picture is significantly **higher** than the scale mean of 3. This applies to both p-values of 0.1, 0.05 and 0.01.
G		The perceived naturalness of this picture is significantly **higher** than the scale mean of 3. This applies to both p-values of 0.1, 0.05 and 0.01.
H		The perceived naturalness of this picture is significantly **lower** than the scale mean of 3. This applies to both p-values of 0.1, 0.05 and 0.01.

Table C8 (continued)

Every picture used in the pre-test, linked to the name (letter) of the picture, as given in Table C7.

I		The perceived naturalness of this picture is significantly **higher** than the scale mean of 3. This applies to both p-values of 0.1, 0.05 and 0.01.
J		The perceived naturalness of this picture is significantly **lower** than the scale mean of 3. This applies to both p-values of 0.1, 0.05 and 0.01.
K		The perceived naturalness of this picture is significantly **lower** than the scale mean of 3. This applies to both p-values of 0.1, 0.05 and 0.01.
L		The perceived naturalness of this picture is significantly **higher** than the scale mean of 3. This applies to both p-values of 0.1, 0.05 and 0.01.
M		The perceived naturalness of this picture is significantly **higher** than the scale mean of 3. This applies to both p-values of 0.1, 0.05 and 0.01.
N		The perceived naturalness of this picture is significantly **lower** than the scale mean of 3. This applies to both p-values of 0.1, 0.05 and 0.01.

Table C9

Descriptive statistics for the likability rating of each picture.

	N	Mean	Std. Deviation	Std. Error Mean
Likability ‘A’	36	1.89	.979	.163
Likability ‘B’	36	2.61	.964	.161
Likability ‘C’	36	3.81	.710	.118
Likability ‘D’	36	2.08	.649	.108
Likability ‘E’	36	3.64	.931	.155
Likability ‘F’	36	3.94	.674	.112
Likability ‘G’	36	3.47	.971	.162
Likability ‘H’	36	2.47	.774	.129
Likability ‘I’	36	3.92	.806	.134
Likability ‘J’	36	1.81	.749	.125

Table C9 (continued)

Descriptive statistics for the likability rating of each picture.

Likability 'K'	36	1.94	.955	.159
Likability 'L'	36	4.22	.760	.127
Likability 'M'	36	4.17	.737	.123
Likability 'N'	36	2.22	.929	.155

Table C10

One-way ANOVA to compare the likability score-means of the 'natural' pictures (all pictures).

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	15.651	6	2.608	4.025	<.001
Within Groups	158.778	245	.648		
Total	174.429	251			

*Note: This table only takes the group of pictures that has a higher perceived naturalness than the scale mean of three, as explained in Table C7, into account. The reason for this is that the 'natural' pictures should have approximately the same average likability scores within the group. The answer-scores of all 36 respondents of this pre-test are analysed through SPSS. Going with an alpha of 0.01, the F-value of 4.025 is **higher** than the critical value of 2.89 (DF numerator = 6, DF denominator = 200). Table C12 and C13 show the one-way ANOVA analyses for the 'artificial' group. The likability differences between both groups and the impact this has on the likeliness to 'act', will be estimated in the questionnaire research.*

Table C11

One-way ANOVA to compare the likability score-means of the 'natural' pictures (pictures minus G).

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	8.634	5	1.727	2.883	.015
Within Groups	125.806	210	.599		
Total	134.440	215			

*Note: Going with an alpha of 0.01, the F-value of 2.883 is **lower** than the critical value of 3.11 (DF numerator = 5, DF denominator = 200).*

Table C12

One-way ANOVA to compare the likability score-means of the 'artificial' pictures (all pictures).

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	19.984	6	3.331	4.445	<.001
Within Groups	183.583	245	.749		
Total	203.567	251			

Note: This table only takes the group of pictures that has a lower perceived naturalness than the scale mean of three, as explained in Table C7, into account. The answer-scores of all 36 respondents of this *pre-test are analysed through SPSS. Going with an alpha of 0.01, the F-value of 4.445 is* ***higher*** *than the critical value of 2.89 (DF numerator = 6, DF denominator = 200).*

Table C13

One-way ANOVA to compare the likability score-means of the 'artificial' pictures (pictures minus B).

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	10.931	5	2.186	3.040	.011
Within Groups	151.028	210	.719		
Total	161.958	215			

Note: Going with an alpha of 0.01, the F-value of 3.040 is ***lower*** *than the critical value of 3.11 (DF numerator = 5, DF denominator = 200).*

Table C14

Paired samples t-test to compare the likability means of the different pictures.

		Mean	Std. Dev.	95% CI of the Difference Lower	Upper	t	df	Two-sided p	Cohen's D
Pair 1	A - B	-.722	1.085	-1.089	-.355	-3.993	35	<.001	-.665
Pair 2	A - D	-.194	.856	-.484	.095	-1.363	35	.182	-.227
Pair 3	A - H	-.583	1.079	-.948	-.218	-3.244	35	.003	-.541
Pair 4	A - J	.083	.692	-.151	.317	.723	35	.475	.120
Pair 5	A - K	-.056	.826	-.335	.224	-.403	35	.689	-.067
Pair 6	A - N	-.333	.676	-.562	-.105	-2.958	35	.006	-.493
Pair 7	B - D	.528	1.000	.190	.866	3.168	35	.003	.528
Pair 8	B - H	.139	.723	-.106	.384	1.152	35	.257	.192
Pair 9	B - J	.806	1.064	.445	1.166	4.542	35	<.001	.757
Pair 10	B - K	.667	1.042	.314	1.019	3.839	35	<.001	.640
Pair 11	B - N	.389	1.022	.043	.735	2.283	35	.029	.381
Pair 12	D - H	-.389	.838	-.672	-.105	-2.786	35	.011	-.464
Pair 13	D - J	.278	.659	.055	.501	2.527	35	.016	.421
Pair 14	D - K	.139	.899	-.165	.443	.927	35	.360	.154
Pair 15	D - N	-.139	.798	-.409	.131	-1.044	35	.304	-.174
Pair 16	H - J	.667	.894	.364	.969	4.472	35	<.001	.745
Pair 17	H - K	.528	.971	.199	.856	3.263	35	.002	.544
Pair 18	H - N	.250	.937	-.067	.567	1.600	35	.119	.267
Pair 19	J - K	-.139	.833	-.421	.143	-1.000	35	.324	-.167
Pair 20	J - N	-.417	.692	-.651	-.183	-3.614	35	<.001	-.602
Pair 21	K - N	-.278	.914	-.587	.031	-1.824	35	.077	-.304
Pair 22	C - E	.167	.811	-.108	.441	1.234	35	.226	.206
Pair 23	C - F	-.139	.931	-.454	.176	-.896	35	.377	-.149
Pair 24	C - G	.333	.986	.000	.667	2.029	35	.050	.338

Table C14 (continued)

Paired samples t-test to compare the likability means of the different pictures.

Pair 25	C - I	-.111	.979	-.442	.220	-.681	35	.500	-.113
Pair 26	C - L	-.417	1.052	-.773	-.061	-2.376	35	.023	-.396
Pair 27	C - M	-.361	.899	-.665	-.057	-2.409	35	.021	-.402
Pair 28	E - F	-.306	.822	-.584	-.027	-2.231	35	.032	-.372
Pair 29	E - G	.167	.971	-.162	.495	1.030	35	.310	.172
Pair 30	E - I	-.278	.974	-.607	.052	-1.711	35	.096	-.285
Pair 31	E - L	-.583	.996	-.920	-.246	-3.513	35	.001	-.585
Pair 32	E - M	-.528	.845	-.814	-.242	-3.749	35	<.001	-.625
Pair 33	F - G	.472	.971	.144	.801	2.919	35	.006	.487
Pair 34	F - I	.028	.774	-.234	.290	.215	35	.831	.036
Pair 35	F - L	-.278	.815	-.553	-.002	-2.046	35	.048	-.341
Pair 36	F - M	-.222	.832	-.504	.059	-1.603	35	.118	-.267
Pair 37	G - I	-.444	.877	-.741	-.148	-3.042	35	.004	-.507
Pair 38	G - L	-.750	.937	-1.067	-.433	-4.801	35	<.001	-.800
Pair 39	G - M	-.694	1.064	-1.055	-.334	-3.915	35	<.001	-.653
Pair 40	I - L	-.306	.856	-.595	-.016	-2.142	35	.039	-.357
Pair 41	I - M	-.250	.732	-.498	-.002	-2.049	35	.048	-.342
Pair 42	L - M	.056	.924	-.257	.368	.361	35	.720	.060

Table C15

Average Cohen's D effect sizes of each picture.

	Average Cohen's D
Picture A	.352
Picture B	.527
Picture C	.267
Picture D	.328
Picture E	.374
Picture F	.275
Picture G	.493
Picture H	.458
Picture I	.273
Picture J	.469
Picture K	.313
Picture L	.423
Picture M	.392
Picture N	.370

Note: These averages are calculated by taking the absolute value of each separate Cohen's D of all pairs that contain a certain picture and dividing it by the amount of pairs that picture appears in.

Figure C3

Set-up of the song title-colour 'matching' question.

Note: respondents were allowed to select multiple options, so that in the end a 'most-fitting' and a 'least-fitting' colour with each song title remained. The most fitting song title-colour match is used in the 'fitting-only' questionnaire, while the least fitting song title-colour match is used in the 'non-fitting-only' questionnaire, as explained in section 8.3.

Table C16

Results of the song title-colour matching question.

Song Titles	Blue	Green	Red	Yellow
Lazy Day	34	6	0	7
Solitude	3	30	6	3
Vivid	2	6	7	31
Rock Bottom	2	25	11	0
Spirit of Life	5	13	4	27
The Enemy	0	0	36	3
Daydream	36	4	0	1
Darkness	0	29	13	0
Reckless	0	1	31	17

Table C16 (continued)

Results of the song title-colour matching question.

Relaxing in Paradise	34	8	0	7
Happiness	13	13	0	30
The Hunt	0	10	32	1

Note: The amount of times that each of the four colours are stated to be 'fitting' with a certain song title by 35 of the respondents. One response was removed, as it contained a missing variable for one of song titles. When JMP gives instructions for the choice-based conjoint to use a specific colour for a given option in a choice set, in the 'fitting-only' questionnaire, one of the titles that has that specific colour as a high-rated colour-match (25 or higher), will be randomly chosen. The other way around, in the 'non-fitting-only' questionnaire, one of the titles that has that specific colour as a low-rated colour-match (6 or lower), will be randomly chosen.

Table C17

Prior estimated probabilities (based on the entered prior means in SAS JMP, as shown in Figure C7).

Respondent choosing…	Prior estimated probability	Opposite prior estimated probability
…blue over green	.562	.438
…blue over red	.679	.321
…blue over yellow	.731	.269
…green over red	.622	.378
…green over yellow	.679	.321
…red over yellow	.562	.438
…natural over artificial	.622	.378
…2 over 1	.622	.378

Note: the 'opposite prior estimated probability' represents the estimation the other way around. For example, the prior estimated probability of a respondent choosing artificial over natural visualisation (instead of natural over artificial) is 0.378. The prior estimated probabilities and opposite prior estimated probabilities always add up to 1.

Table C18

Outliers based on response-timing

	SA-Q1	SA-Q2	SA-Q3	SA-Q4	SA-Q5	SA-Q6	SA-Q7	SA-Q8
1	0.76	0.755	0.758	0.728	0.736	0.77	0.738	0.735
2	0.761	0.758	0.76	0.751	0.737	0.773	0.751	0.74
3	0.762	0.76	0.765	0.769	0.755	0.776	0.753	0.764
4	0.766	0.764	0.766	0.774	0.757	0.776	0.754	0.769
5	0.766	0.765	0.768	0.778	0.758	0.782	0.758	0.771
6	0.77	0.768	0.773	0.78	0.758	0.785	0.764	0.775
7	0.775	0.771	0.776	0.785	0.764	0.787	0.767	0.78

Table C18 (continued)

Outliers based on response-timing

8	0.778	0.772	0.779	0.791	0.767	0.791	0.775	0.781
9	0.779	0.781	0.78	0.794	0.781	0.793	0.779	0.784
10	0.784	0.785	0.783	0.795	0.79	0.797	0.781	0.785

	SB-Q1	SB-Q2	SB-Q3	SB-Q4	SB-Q5	SB-Q6	SB-Q7	SB-Q8
1	0.772	0.76	0.73	0.761	0.736	0.763	0.731	0.751
2	0.774	0.762	0.739	0.762	0.754	0.766	0.738	0.754
3	0.776	0.765	0.758	0.762	0.765	0.768	0.753	0.756
4	0.78	0.767	0.763	0.765	0.766	0.771	0.757	0.756
5	0.782	0.771	0.766	0.77	0.772	0.778	0.763	0.762
6	0.785	0.773	0.768	0.778	0.774	0.781	0.765	0.763
7	0.787	0.778	0.771	0.78	0.775	0.783	0.768	0.768
8	0.792	0.779	0.774	0.784	0.781	0.79	0.774	0.772
9	0.795	0.781	0.786	0.787	0.781	0.791	0.776	0.779
10	0.8	0.785	0.789	0.789	0.782	0.793	0.786	0.787

Note: of all conjoint experiment questions in the fitting survey (SA) and the non-fitting survey (SB), the quickest ten replies can be seen in the table. The 11 respondents who accounted for an outlier (marked red) were completely removed from the dataset. These respondents had an answer that was so quick that it fell outside the lower boundary of the 2σ-range from μ and thus was quicker than 0.741 seconds. The reason that only the fastest ten replies were taken into account for every question, when calculating σ and μ, is that there are also very slow answers in the dataset, that took respondents up to 200 seconds. These outliers are not removed, as some respondents could have had problems with their internet connection while taking the questionnaire, or they could just take their time to pick a choice option. Taking these replies into account when calculating σ and μ would not give accurate results for the quick responses in the survey. Therefore, the outlier removal of unrealistically fast responses focused only on 'the quickest of the quickest'.

Figure C4

Bar graph, depicting the age distribution among the conjoint experiment respondents.

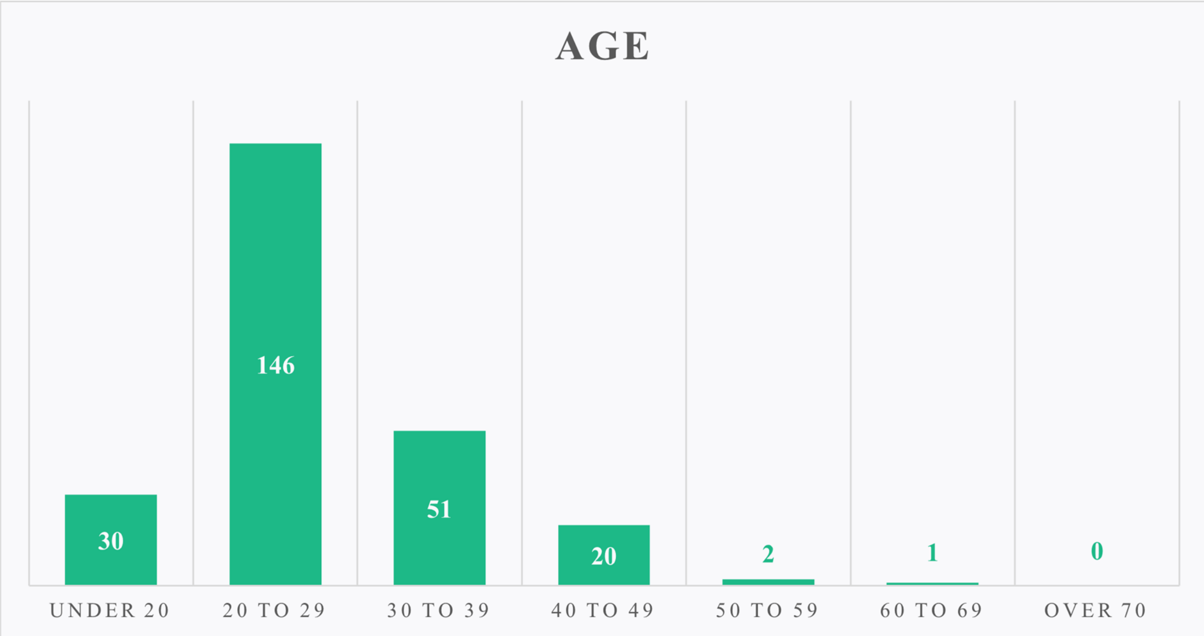


Figure C5

Bar graph, depicting the gender distribution among the conjoint experiment respondents.

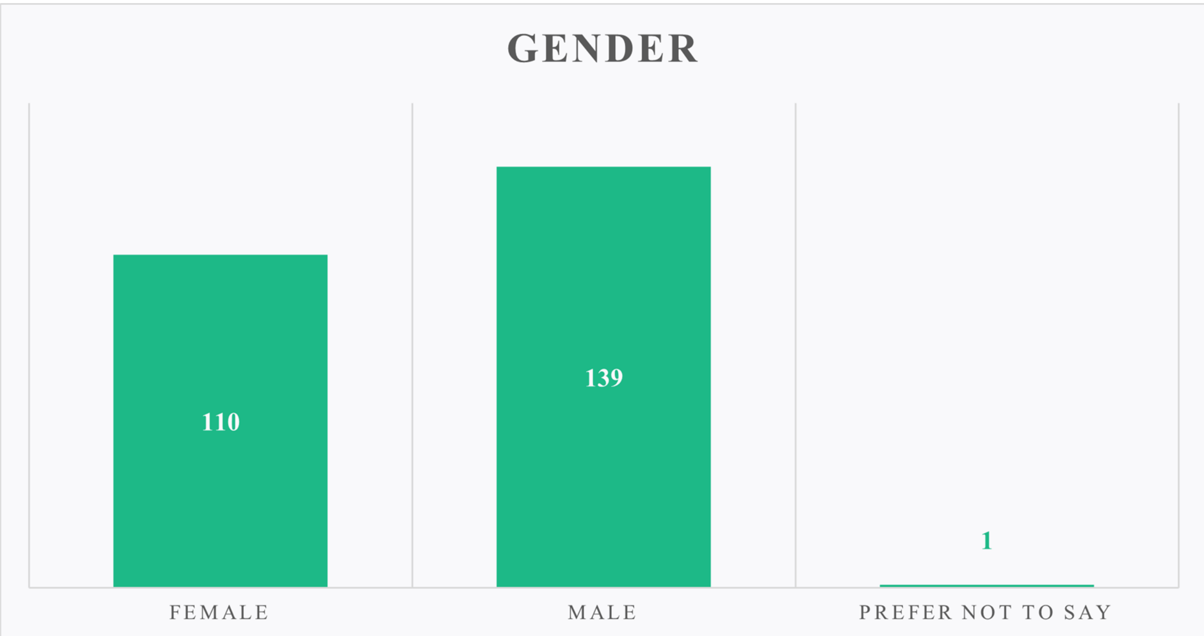


Figure C6

Bar graph, depicting the preferred 'MDS' distribution among the conjoint experiment respondents.

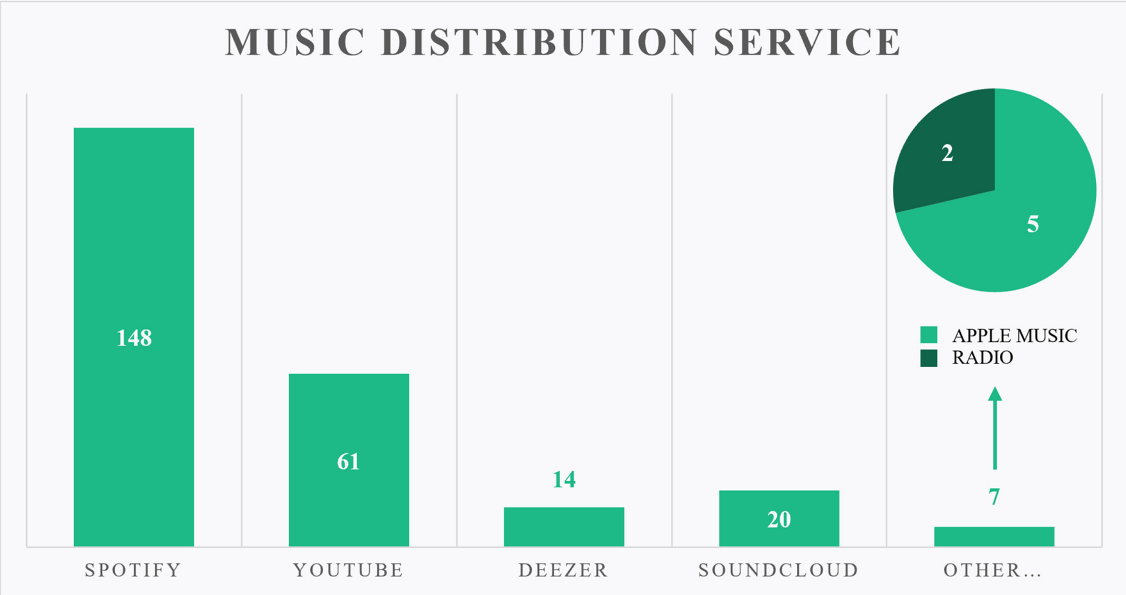


Figure C7

Conjoint experiment design in SAS JMP.

Choice Design

Attributes

Name	Role	Attribute Levels			
Color	Categorical	Yellow	Red	Green	Blue
Visualization	Categorical	Artificial		Natural	
Number of Artists	Categorical	1		2	

Model

Prior Specification

☐ Ignore prior specifications. Generate the Utility Neutral design.

Prior Mean

Effect	Prior Mean
Color 1	-0,50
Color 2	-0,25
Color 3	0,250
Visualization	-0,50
Number of Artists	-0,50

☐ Ignore prior variance. Generate the local design for the prior mean.

Prior Variance Matrix

Effect	Color 1	Color 2	Color 3	Visualization	Number of Artists
Color 1	1,000	0,000	0,000	0,000	0,000
Color 2		1,000	0,000	0,000	0,000
Color 3			1,000	0,000	0,000
Visualization				1,000	0,000
Number of Artists					1,000

Design Generation

3 Number of attributes that can change within a choice set

3 Number of profiles per choice set

8 Number of choice sets per survey

1 Number of surveys

125 Expected number of respondents per survey

Make Design

Back

Note: the attributes and their levels, the prior means and the design generation section are filled in, to obtain the desired choice-based conjoint experiment. The 'design generation' section was filled in, following the 'design of experiment guide' on the website of JMP Statistical Discovery (2021).

Figure C8

Obtained design of the conjoint experiment from SAS JMP.

Choice Design

Attributes

Name	Role	Attribute Levels			
Color	Categorical	Yellow	Red	Green	Blue
Visualization	Categorical	Artificial		Natural	
Number of Artists	Categorical	1		2	

Design

Choice Set	Color	Visualization	Number of Artists
1	Red	Natural	2
1	Yellow	Artificial	2
1	Green	Natural	1
2	Red	Natural	1
2	Green	Artificial	1
2	Yellow	Artificial	2
3	Blue	Natural	1
3	Red	Artificial	2
3	Yellow	Artificial	1
4	Blue	Artificial	1
4	Green	Natural	2
4	Red	Natural	2
5	Green	Natural	2
5	Yellow	Natural	1
5	Red	Artificial	2
6	Yellow	Natural	2
6	Red	Natural	1
6	Green	Artificial	2
7	Blue	Artificial	2
7	Red	Artificial	1
7	Yellow	Natural	2
8	Yellow	Artificial	2
8	Blue	Natural	2
8	Green	Natural	1

○ Output separate tables for profiles and responses
◉ Combine profiles and responses in one table

Make Table

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Note: every row in the 'design' section represents a choice option, while every three consecutive options form a choice set. For example, a red coloured cover, with a natural image and two artists would be the first choice option.

Table C19

Probability profiler grid table of the 'non-fitting-only' part of the conjoint experiment.

Option	Colour	Visualisation	Number of Artists	Probability
1	Yellow	Artificial	1	0.1243720831
2	Yellow	Artificial	2	0.1823544561
3	Yellow	Natural	1	0.2202320523
4	Yellow	Natural	2	0.3072244107
5	Red	Artificial	1	0.100266473
6	Red	Artificial	2	0.1489220979
7	Red	Natural	1	0.1813959411
8	Red	Natural	2	0.2581260301
9	Green	Artificial	1	0.1434417849
10	Green	Artificial	2	0.2082005943
11	Green	Natural	1	0.2498065845
12	Green	Natural	2	0.3433372955
13	Blue	Artificial	1	0.2425892831
14	Blue	Artificial	2	0.3346230814
15	Blue	Natural	1	0.3890785981
16	Blue	Natural	2	0.5

Note: the probability of a consumer picking a certain option over the baseline option (option 16).

Table C20

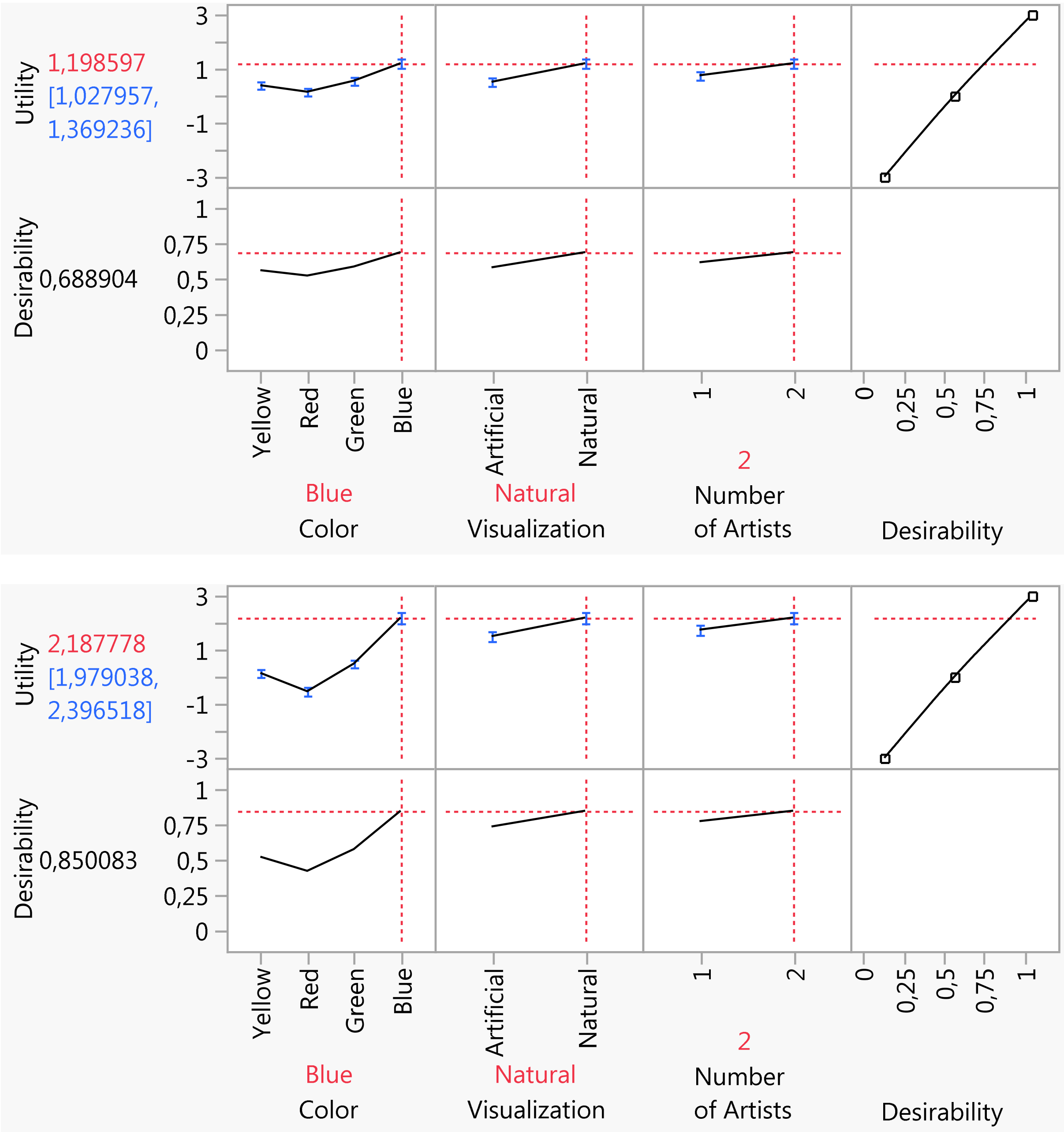
Probability profiler grid table of the 'fitting-only' part of the conjoint experiment.

Option	Colour	Visualisation	Number of Artists	Probability
1	Yellow	Artificial	1	0.0395487928
2	Yellow	Artificial	2	0.0607290927
3	Yellow	Natural	1	0.07568177
4	Yellow	Natural	2	0.1139178424
5	Red	Artificial	1	0.0206405264
6	Red	Artificial	2	0.0320322557
7	Red	Natural	1	0.0402217872
8	Red	Natural	2	0.0617393399
9	Green	Artificial	1	0.0551933564
10	Green	Artificial	2	0.0840191455
11	Green	Natural	1	0.1040709079
12	Green	Natural	2	0.1542561686
13	Blue	Artificial	1	0.2425892831
14	Blue	Artificial	2	0.3346230814
15	Blue	Natural	1	0.3890785981
16	Blue	Natural	2	0.5

Note: the probability of a consumer picking a certain option over the baseline option (option 16).

Figure C9

Utility profiler with the attribute-levels that provide a maximised desirability.



Note: highlighted in red, the attribute-levels that provide the highest possible desirability are shown. Desirability is referred to in JMP in the manner intended by Derringer and Suich (1980): 'a desirable combination of properties'. Important to state is that the desirability of 0.85 that is shown in the lower part of this figure is only reached when the fitting responses are taken into account. When only taking the non-fitting responses into account, the desirability is 0.689, as can be seen in the higher part of the figure. This clearly shows that the preferred attribute-level of the fitting versus non-fitting attribute is 'fitting'.