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Show Your Face! Investigating the Relationship Between Human Faces and Music's Success

Michael Schlechtinger
University of Siegen, michael.schlechtinger@uni-siegen.de

Michael Klesel
University of Siegen, michael.klesel@uni-siegen.de

Bjoern Niehaves
University of Siegen, bjoern.niehaves@uni-siegen.de

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Completed Research

Michael Schlechtinger
University of Siegen
michael.schlechtinger@uni-siegen.de

Michael Klesel
University of Siegen and
University of Twente
michael.klesel@uni-siegen.de

Bjoern Niehaves
University of Siegen
bjoern.niehaves@uni-siegen.de

Abstract

Streaming services are becoming the primary source for media consumption. Particularly platforms like SoundCloud, where users can disseminate user-generated content (UGC), are gaining relevance. To shed light into the drivers which positively influence the number of listeners, we draw from marketing literature related to depictions of people, which suggests that human faces can contribute to a higher degree of brand liking or brand identification. Thereupon, we propose a hypothesis which suggests that human faces on cover arts likewise generate more plays. We follow a data science approach using 1754 observations from SoundCloud and apply Google's facial recognition API (Vision AI) to examine the impact of human faces on music's success. We provide initial evidence that tracks with a human-face cover art yield in a higher number of plays compared to tracks with a cover art without a human face.

Keywords

Data Science, SoundCloud, Cover Arts, Human Faces, UGC, MGC, Streaming, Vision AI

Introduction

Streaming platforms have widely replaced traditional forms of media consumption. In fact, current studies suggest that in 2018, over 46 percent of the revenue in the music industry was generated by means of streaming services (International Federation of the Phonographic Industry 2019). A major reason for the attractiveness of streaming platforms relates to the fact that they offer a great variety of constantly available content (Herbert et al. 2019) including opportunities to consume international media as well. In contrast to physical media or media downloads, streaming services can usually be paid by a subscription fee or a freemium model (Mäntymäki and Najmul Islam 2015).

Some of these platforms allow their users, commonly referred to as content creators, to create, upload, and share their own user-generated content (UGC). Compared to classic music retail or marketer generated content (MGC) focused platforms like Spotify, UGC-platforms such as SoundCloud commonly eliminate the need for an intermediate by allowing users to upload their music for free. Existing literature on UGC mainly consults the video platform YouTube, analyzing the influence of content creators' personality (Ferchaud et al. 2018), or video uploading activity (Saurabh and Gautam 2019) on user engagement indicators.

While previous literature has contributed to a better understanding of streaming platforms in general, insights in terms of critical success factors of UGC-platform are scarce. In light of an increasing number of users of streaming platforms and a significant interest in UGC platforms, addressing this gap is helpful for artists and platform providers alike. Hence, we draw from established literature on UGC, as well research

on depictions of people and faces in marketing which suggest a positive impact on factors like brand liking when faces are used in advertisement. In specific, we analyzed the impact of cover arts on the charting position, distinguishing tracks with and without human faces.

The remainder is structured as follows: First, we review existing literature on different types of streaming highlighting both established areas research and areas that are now well-understood yet. Second, we propose a hypothesis that allows us to shed further light into the role of human faces on cover arts and their impact on the number of plays. Third, we describe our methodological approach to investigate our hypothesis and present the results. Fourth, we discuss our findings, highlight the boundaries of our study, and conclude with promising avenues for future research.

Related Work

Streaming

Although the first appearance of 'streaming media' can be traced back to the 1990s, the term is oftentimes used ambiguously in previous literature. Studies with an emphasis on technological aspects published in the early 2000s primarily focus on the underlying processes (Wu et al. 2001). Current literature has shifted their attention towards non-technological issues. Researchers use the term in a sense of interconnectivity, emphasizing the ability to access a vast catalog of media with all kinds of devices, collapsing boundaries among distribution, exhibition and consumption (Hesmondhalgh and Meier 2018). In essence, it describes a process of delivering media over the internet in 'real-time', without the file being downloaded or stored on a local drive. This inhabits lots of advantages for the music industry. As several studies suggest, streaming music has dampened the attrition from licensed digital downloads (i.e., the piracy effect) about 7 percent every year, in consequence of cognitive and annoyance costs associated with consuming unlicensed digital music (Chellappa and Shivendu 2003; Khouja et al. 2008; Koh et al. 2019; Sundararajan 2004). Streaming in a contemporary sense, however, refers to a media service that is constantly available for on-demand access with a media catalog of different sizes, usually compensated by a subscription fee (Herbert et al. 2019).

Based on new business models, including freemium models, the interest in streaming services has increased significantly (Niemand et al. 2015). Next to the subscription fee (e.g., 10 USD per month), online-based services can earn revenue in another way: they can rely on advertising as a revenue source (Halbheer et al. 2014). Many firms (e.g., Spotify, Deezer) operate a two-tiered service that simultaneously offers a free ad-based version as well as a fee-based version (Riggins 2002).

Especially within the music industry, renowned types of media consumption increasingly show decrepitude regarding their revenues; not only attributed to the rising competition of piracy (Aguiar and Waldfogel 2018; Koh et al. 2019; Sundararajan 2004) but also due to streaming services becoming more and more relevant. The International Federation of the Phonographic Industry (IFPI), representing the interests of 1,300 record companies, documents a streaming market share of 46,9% compared to global music revenues (International Federation of the Phonographic Industry 2019). Streaming has developed into the primary way consumers invest in the medium, resulting in a steady upward trend since 2011. Being aware of that fact, content creators more and more try to distribute their art through these services.

UGC and MGC

Content can be distributed as UGC and MGC (Goh et al. 2012; Li et al. 2017). Current research frequently refers to UGC as unpaid, thus not company-affiliated information, produced by individuals. Therefore, UGC often includes judgments, opinions, perceptions, and beliefs sought to help solving a problem collectively (Claussen et al. 2013; Doan et al. 2011; Love and Hirschheim 2017; Lukyanenko et al. 2019; Prpić et al. 2015; Yoo and Kim 2012). In the context of streaming services, we define UGC as:

> *Content that is created by individuals (content owners) who can distribute their work independently (Eiriz and Leite 2017) as well as directly interact with consumers (Lee et al. 2017).*

In contrast, MGC is represented through marketers, who generate content on behalf of their organizations with the primary objective to engage users. In the context of streaming services, we define MGC as:

Content that is created by individuals (content owners) who can only distribute their product to MGC-services intermediated through specific distribution services or aggregators (Galuszka 2015). These aggregators allow independent content creators to publish their work to MGC-services (usually coupled with a fee).

These two forms of content generation also apply to data being distributed through streaming services. In Table 1 we present different types of content generation (i.e., UGC and MGC) as well as different types of media (i.e., audio and video) that have been investigated by previous research. Moreover, we included how previous literature collected empirical data by distinguishing self-reported measures (e.g., survey data) and objective measures (e.g., archival data).

<table>
<tr><td rowspan="10">MGC</td><td colspan="2">Netflix (Video)</td><td colspan="2">Spotify (Audio)</td></tr>
<tr><td>Self-Reported</td><td>(Fernández-Robin et al. 2019; Oyedele and Simpson 2018)</td><td>Self-Reported</td><td>(Mäntymäki and Najmul Islam 2015; Morris and Powers 2015; Niemand et al. 2015; Oyedele and Simpson 2018)</td></tr>
<tr><td rowspan="9">Objective</td><td rowspan="9">(Herbert et al. 2019; Pant and Yu 2018; Sahoo et al. 2012)</td><td>Objective</td><td>(Herbert et al., 2019), (Aguiar & Waldfogel, 2018; Schwind et al., 2018; Skog, Wimelius, & Sandberg, 2018)</td></tr>
<tr><td colspan="2">Pandora (Audio)</td></tr>
<tr><td>Self-Reported</td><td>(Oyedele and Simpson 2018)</td></tr>
<tr><td>Objective</td><td>(Aguiar and Waldfogel 2018; Koh et al. 2019)</td></tr>
<tr><td colspan="2">Apple Music (Audio)</td></tr>
<tr><td>Self-Reported</td><td>(Morris and Powers 2015)</td></tr>
<tr><td>Objective</td><td>(-)*</td></tr>
<tr><td rowspan="3">UGC</td><td colspan="2">YouTube (Video)</td><td colspan="2">SoundCloud (Audio)</td></tr>
<tr><td>Self-Reported</td><td>(Ferchaud et al. 2018; Orús et al. 2016; Zimmermann and Jucks 2019)</td><td>Self-Reported</td><td>(Birch 2017)</td></tr>
<tr><td>Objective</td><td>(Aguiar and Waldfogel 2018; Gandomi and Haider 2015; Saurabh and Gautam 2019)</td><td>Objective</td><td>(Bruns et al. 2018; Hubbles et al. 2017; Ross et al. 2018)</td></tr>
<tr><td colspan="4">*As for now, this service does not support a public API or share content-related statistics.</td></tr>
</table>

Table 1. Streaming services distinguished by UGC and MGC criteria

Table 1 shows that a substantial body of research on streaming services has investigated different types of media (i.e., video and audio). With regards to video platforms, a large number of studies investigated the MGC platform Netflix. Most of the given research in this sector consists of survey data to analyze user's behavior in terms of watch time or personal watch (e.g., Fernández-Robin et al. 2019; Sahoo et al. 2012). YouTube, one of the most successful video streaming services in the UGC segment (Gandomi and Haider 2015; Orús et al. 2016) has been widely investigated in various studies. The research concerning YouTube, seeks to ascertain the phenomena of successful social content (Saurabh and Gautam 2019; Susarla et al. 2012) or attest a main role in outweighing losses of piracy by the earned gains in streaming revenue (Aguiar and Waldfogel 2018). The literature concerning Spotify focusses on its business model, especially the

freemium alternative (Mäntymäki and Najmul Islam 2015; Niemand et al. 2015) as well as Spotify's architecture (Schwind et al. 2018; Skog et al. 2018). Compared to the other streaming services considered, the UGC-audio uploading, streaming, and sharing website SoundCloud has been scarcely investigated so far. Notable exceptions include studies that collected and analyzed comments expressed on the site (Hubbles et al. 2017) or studies examining SoundCloud for bot activity (Bruns et al. 2018; Ferrara et al. 2016; Ross et al. 2018).

In summary, we conclude that numerous studies have been conducted in the domain of streaming services. However, research considering UGC-music-distribution platforms lacks insights on tangible actions that allows platform providers and music producers to successfully increase a track's success. Against this background, we propose a research hypothesis that seeks to contribute to a better understanding of the success factors by considering the role of cover arts.

Hypothesis Development

We draw from previous literature on depictions of people in marketing to investigate the role of faces in the context of music streaming services. Although they are used in most visual marketing such as advertisements and in-store marketing, we often fail to reflect on the presence of depictions of people (Aydınoğlu and Cian 2014; McQuarrie 2008; Wedel and Pieters 2008). Thus, scholars studied the consumer responses to photographs of people in marketing for many years (Baker and Churchill 1977; Caballero and Solomon 1984), revealing that images can influence buying behavior positively, if the person used in the advertisement has the opposite sex or a certain degree of attractiveness. Lachance et al. (1977) on the other hand, depict that models solely facilitate recognition of model-related information, but do little to increase the recognition of brand names.

While the presented literature centers on depictions of people as a whole, important characteristics, needed to recognize a person, relate to their faces. They are more likely to attract our attention than common objects (Ro et al. 2001). The preference to look at human faces is already established in infants (Johnson et al. 1991). Literature also shows that facial expressions, emotional and threatening expressions in particular, evoke enhanced processing (Palermo and Rhodes 2007). With the help of functional magnetic resonance imaging, neuro scientists identified the "fusiform face area" in the human brain, which is specialized in face processing (Haist and Anzures 2017). Moreover, eye-tracking studies have demonstrated that human faces, attract more visual attention than other objects in advertisements (Ju and Johnson 2010).

Brands frequently utilize the demonstration of faces in connection with the brand name as a promotional mean in order to strengthen and distinguish brands (Erdogan and Drollinger 2008; Johar et al. 2005), position themselves (Orth and Malkewitz 2012), to gain viewer attention (Pieters and Wedel 2004), or to build brand equity (Park et al. 2010). Although a deep relationship with a brand hinges on extended interactions (Batra et al. 2012), initial liking begins in the early stages of brand encounter; where visuals, including faces, play a key role to increase brand liking (Orth et al. 2017). Content creators or artists can be thought of as brand managers, as they are actively engaged in developing, nurturing and promoting themselves as recognizable "products" (Schroeder 2005). Similar to previous studies, we assume that similar effects also occur in our research setting. In specific, we assume that the effects of human faces are also relevant in the context of UCG platforms. Therefore, we draw from established relationships between faces and brand liking (Orth et al. 2017) and propose the following hypothesis:

Hypothesis: *Tracks using a cover art with human faces have a higher score compared to tracks using cover arts without a human face.*

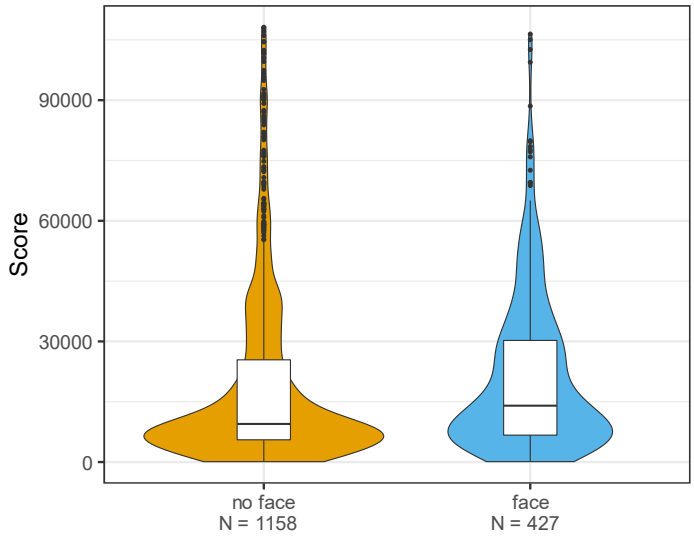
Methodology

In order to test our hypothesis, we follow a data science approach following guidelines proposed by Müller et al (2016). We chose this approach because we analyze large, diverse, and dynamic sets of UGC. In the following chapter, we will introduce the methods we used in order to gather, analyze and evaluate the data. We will provide insights into the data collection process by addressing the requirements for a web scraping script and the resulted data points. On this basis, we will examine the influence of faces on cover arts on the score of a charting track.

We used a web scraping script to collect data from SoundCloud. As Soundcloud's API does not offer a service to provide random tracks, we collected data from the top 80 charting tracks in every genre (which is the maximum of tracks per charting genre), resulting in 1754 data points (some charting genres did not offer the full 80 tracks). For each individual track, we collected and associated the requested resources by querying the API. The script was run once for every genre in May 2019. We removed tracks that do not have a cover art (120 observations) and enriched the remaining data with facial analysis information obtained by requesting Google's "Vision AI".

We operationalized scores using the score index provided by SoundCloud's API. The score reflects the overall plays of a tracking during the last week (i.e., weekly plays). This index is used as the performance indicator within every genre to rank tracks and is thus considered a reliable indicator to reflect the success of an individual track. Faces were operationalized using the information gained by the Vision AI. Based on our data, an average of 0.4 faces were recognized by the API (M = .44, SD = .98).

Descriptive statistics show that there are observations that protrude from the crowd based on a significantly higher score (M = 105173, SD = 321263.8). Consequently, the range of the score is also very high (Min = 93, Max = 5439924). This is not surprising, as SoundCloud is used by artists who already gained much attention (e.g., Roddy Rich). Since we seek to better understand the role of cover arts, we focus on the main body of tracks, thus, exclude tracks with very high scores. We use the Interquartile Rule for each group to identify those and excluded 302 observations yielding in N = 1585 observations in total (sample of interest). An overview of the descriptive statistics for the total sample and the sample of interest is shown in Table 2.



		N	*M*	*SD*	Median	Min	Max	Skew	Kurtosis
total data	face	568	148,683	336,438	25,134	102	3,217,112	4.19	22.98
	no face	1,319	86,437	312,775	11,838	93	5,439,924	8.70	104.61
	total	1,887	105,174	321,264	14,719	93	5,439,924	7.08	73.50
sample of interest	face	427	21,272	19,655	14,021	102	106,454	1.54	2.60
	no face	1,158	18,953	21,683	9,474	93	108,137	1.89	3.39
	total	1,585	19,578	21,175	10,552	93	108,137	1.81	3.20

Table 2. Descriptive statistics

Based on the descriptive statistic, we observe differences between tracks with faces (M = 21,271) and without faces (M = 18,953). The same conclusion can be drawn using the median with a median score of 14,021 for tracks with faces and 9,473 for tracks without faces. To increase the reliability of these differences, we proceed with inferential statistics to test for differences in the population.

Since the score data and the residuals are not distributed normally (Shapiro-Wilk normality test, ps < .001), but has variances across both groups (Levene's Test for homogeneity of variance, p = .73), we apply a Wilcoxon rank sum test, which is known to be robust against unequal distributions across groups. The results suggest a significant difference (W = 280812, p < .001). To ensure the robustness of the results we did the same analysis for equal observations in each group drawing 427 random samples from the "no face" group yielding in similar results (Shapiro-Wilk normality test, ps < .001, Levene's Test for homogeneity of variance, p = .50, Wilcoxon rank sum test, W = 105596, p < .001).

To obtain further insights into the role of faces in cover arts, we conducted an additional post-hoc analysis to investigate whether the number of faces is also relevant with regards to the score and conducted a non-parametric test procedure for multiple comparisons. In specific, we applied the Conover-Iman test (1979) and an adjustment as suggested by Hochberg (1995). The Kruskal-Wallis χ^2 test is significant (2, N = 1585) = 23.90, p < .001. The results show that cover arts with no faces have a lower score than tracks with one face (t = -2.312 (p = .010)) and multiple faces t(-4.636 (p < .001)). Moreover, tracks with one face have a lower score compared to tracks with multiple faces t(-2.596 (p = 0.005)).

Discussion

In this paper, we aim to extend UGC-research with implications gathered from marketing research considering faces on cover arts. Using data from SoundCloud's charts, we provide initial evidence that cover arts containing faces do yield in higher scores compared to tracks without faces. To demonstrate the impact of our findings, we reflect our results with a monetary perspective. According to Soundcharts.com (Soundcharts 2019), \$0,0032 is payed per stream to the artist on Spotify. Since it is unclear, what is paid on SoundCloud, we use this number for the following example. Based on our results, the difference in terms of the median between both groups is 4,547 (Mdn_{face}: 14,021 - Mdn_{noface}: 9,474). Consequently, an artist that uses a cover art with a face can earn approximately \$14,55 per week and approximately \$756,60 a year (52 weeks) more per song compared to a cover art without a face. Considering that artists usually release their songs on multiple streaming services offering better rates, this could result in a tremendous difference in income not including mechanical royalties or merchandise earnings. Therefore, it seems worthwhile to consider faces in the design and merchandising of cover arts.

Based on these results, we derive several implications. Our findings are in line with research on depictions of people in marketing. The attention-attracting influence which is caused by faces (Haist and Anzures 2017; Ju and Johnson 2010; Ro et al. 2001) can also be linked to our study, which provides initial evidence for this kind of effect. The portrayed effect does furthermore seem to be a factor in consumer music selection behavior. Thus, our study extends our knowledge of the role of faces in the context of music streaming services, rendering the importance of faces in marketing relevant for music marketing. We also provide initial evidence that insights from brand marketing research can be transferred to artists or content creators as depicted by Schroeder (2005). By quantifying the impact of cover arts, we created a link between faces as a representation of a brand towards faces as a representation of an artist. Thus, a major takeaway from this study is the largely ignored impact of cover arts on (a brand's) music's success. This insight can be of primary guidance for artists as it encourages them to make use of faces in cover arts. A continuous usage of faces in an artist's marketing persona could not only introduce new people to the content, but also strengthen the existing relationship with listeners (Erdogan and Drollinger 2008). Platform providers on the other hand could use our insights to improve music recommendation algorithms.

Limitations and Outlook

As every study, the results are beset with limitations which opens the door for future research. Our results should be carefully interpreted in the light of our sample. Since our data is exclusively from one platform, there are limitations with regard to the generalizability. Also, we cannot draw conclusions in terms of variations across time. There are also limitations in terms of the classifications of faces. While the Vision AI is well-suited for batch processing, the identification of faces can be erroneous. Therefore, it is

recommendable to conduct further research that gives insights into the performance of the API with regards to correct classification.

While this study provides evidence of a link between human faces and music success, the underlying mechanism remains unclear so far. Consequently, we suggest that future research could use existing constructs to get further insights. For instance, Cyr et al. (2009) establish that websites containing human images, including facial features, yield a higher degree of social presence compared to websites not containing human faces. Furthermore, research suggests using humanoid embodiment to significantly influence user's perceptions of social presence in the domain of online product recommendation agents (Qiu and Benbasat 2009). Consequently, users' trusting beliefs, perceptions of enjoyment, and ultimately, their intentions to use an agent as a decision aid are reinforced. These insights are promising perspectives to unveil underlying relationships that are responsible for variations documented here.

The focus on detecting faces within cover arts offers potential for future research. Image and facial analysis APIs usually offer more than just binary information about a mere existence of a face, such as the facial expressions. Future studies could use facial expression data to analyze listener's reaction towards those. In order to provide robust data, future studies could triangulate the results by means of collecting additional, self-reported data on the influence of human faces on cover arts. These could present new insights into various of the recited hypothesis, such as the correlations of a face's attractiveness and a track's success (Baker and Churchill 1977; Caballero and Solomon 1984) on a streaming platform.

In this context, there are various confounding factors that we did not include so far. For example, the artist's prominence could have an impact on the score. Particularly, newcomer's who have a small but reliable community could have different drivers that stimulate the number of plays. Furthermore, we did not check for the influence of social bots. Thus, user engagement indicators could have been artificially inflated to promote the track to a larger audience. To address these shortcomings, future research could control for similar comments or rapid accumulations of user engagement indicators.

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