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Generative AI-Enabled Music Generation in Marketing and Consumer Response

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Abstract

Generative AI is revolutionizing the marketing industry by producing high-quality, cost-effective, and time-efficient content. This study investigates the potential of AI-generated music in digital advertising. Two studies, a survey and a real-world A/B test, evaluate different songs on chosen criteria: *Overall, Melodiousness, Creativity, Naturalness, Correctness, and Prompt Following* for the survey, and click-through rates (CTR) for the field experiment. The survey results show that AI-generated music can be comparable in quality to human compositions, even scoring significantly higher in the categories *Prompt Following* and *Melodiousness*. However, AI music showed significantly worse results in the category *Creativity*. The field experiment revealed no statistically significant difference in CTR between advertisements using AI-generated and royalty-free music, demonstrating that AI music can be a good substitute in supporting roles. This research underlines the possibility for AI-generated music to be used in hyper-personalized advertising, while addressing challenges related to perceived creativity and copyright. The findings contribute to understanding AI's disruptive potential in marketing and offer practical insights for integrating AI tools effectively.

Keywords: AI-generated music; music in advertising; AI consumer response

1 Introduction

Generative AI has made significant advancements in recent years. Especially in creative fields it hast become indistinguishable to human made art for most people (Bellaiche et al., 2023). The introduction of ChatGPT, at the end of 2022, was a turning point that is revolutionizing many industries, including marketing. After that there were many new and innovative AI tools with most of them being widely available to the public. In the creative domain, text-to-image tools such as DALL-E, Midjourney, Firefly or Google's Imagen have been able to produce highly effective marketing images. These even outperformed traditional image sources, such as stock images and freelancers, at a fraction of the cost (Hartmann et al., 2024).

With this in mind, and the release of highly sophisticated and easily accessible music generation tools such as Suno AI, Udio AI or StableAudio, the question arises whether AI-generated music can be equally effective for marketing purposes. Music in marketing is very common. According to a study by (Allan, 2008), 94% of prime-television advertisements contained music. And since the global music market has significantly grown since then, it is safe to say that this number is more likely to have increased rather than decreased (IFPI, 2024). But advertisements aren't the only way brands utilize music in their marketing. Most retail stores strategically play music to increase sales as it can make goods and services more appealing which "helps create a bridge between the customer and the product" (Neese, 2015). While the use of music in retail stores is an interesting subject, and the potential of AI-generated music in this context is certainly worth exploring, this paper will focus on its application in online advertisement campaigns.

Music licensing is a complex subject that I won't go too deeply into in this paper. However, it is important to note a few key points. Factors such as the popularity of the song, the duration of use, and the platform on which it will be utilized all influence the cost of a music license. Although it is challenging to generalize licensing fees, they can often represent a significant expense in a company's marketing budget (AudioNetwork, 2023). The rise of AI-generated music offers a promising alternative to help avoid the high costs and legal complexities associated with music licensing. Additionally, AI music can be produced quicker than traditional music. This could, for example, enable hyper-personalized advertisements and in-store music experiences. This has the potential to be highly impactful, as personalized advertisements are often more effective in engaging consumers (Monem, 2021).

When discussing music made by generative AI it is also worth mentioning the complications it brings to the topic of originality and copyright. The questions arises if AI-generated works can be considered truly original. This is particularly important when considering copyright laws, which have traditionally protected works based on their originality and the creator's expression (Fenwick & Jurcys, 2023). Especially, since some of the training data used by the

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most sophisticated AI music generation tools remain undisclosed. Although AI-generated music offers faster and more cost-effective solutions (Lin & Chen, 2024), it challenges these conventional notions of authorship. This development highlights the need for evolving legal frameworks that can balance human-made music with the creations made by AI.

Existing research has mainly focused on the effects of music in marketing in general or the different approaches to generating music using AI, which we will both discuss in the next chapter. Little has been said about the potential effectiveness of AI-generated music in marketing. The role of AI as a disruptive technology in marketing has been explored by various studies, including the 2024 paper by Jochen Hartmann, Yannick Exner, and Samuel Domdey, titled "*Can Generative AI Create Superhuman Visual Marketing Content?*". As this paper aims to address a similar question but for auditory marketing, it draws inspiration from (Hartmann et al., 2024), with the aim of producing equally insightful results.

To achieve this, a two-part survey and a real-life A/B test comparing AI-generated music with traditionally made music will be conducted. The first part of the survey will explore basic consumer attitudes toward AI-generated music. In the second part of the survey participants will listen to short snippets of music, both AI-generated music and music made by a professional musician, and evaluate them based on various criteria. I have selected the metrics outlined by (Chu et al., 2022), but instead of using all nine metrics, I have condensed them into the six most relevant: *Overall, Creativity, Naturalness, Melodiousness, Correctness,* and *Coherence (Prompt following)*. To make it as fair as possible, the various AI tools and the musician will be given the exact same instructions in the form of a text prompt. In line with (Chu et al., 2022), I aim survey novice users without professional musical expertise. Overall, the song generated with Suno AI scored significantly higher values for two out of the six metrics compared to the human-made song, while only scoring significantly worse in one. It also had the highest cumulative mean score, surpassing the human composition as well as the song generated with StableAudio, which ranked last.

For our A/B test, we will compare an AI-generated song with a royalty-free song that shares a similar vibe. To evaluate the effectiveness of these tracks, we will run Facebook and Instagram advertisements, one version with AI-generated music and the other with royalty-free music, under otherwise identical conditions (ceteris paribus). By analyzing Meta's built-in insights, we will compare key metrics, with a focus on the click-through rate (CTR) of both advertisements. The data revealed no significant difference between both advertisements CTR.

The evaluation of these two experiments will provide valuable insights into human perception of AI-generated music. It will also reveal whether low-cost, off-the-shelf AI music generation tools are already sophisticated enough to match or even exceed the quality of traditionally composed music. If so, this paper will showcase yet another example of how AI is revolutionizing the marketing industry. Additionally, we will identify the strengths and weaknesses of AI-generated music, as well as the top-performing tools currently available. From this, best practices can be established. (Davenport et al., 2019).

In the next chapter, I will conduct a comprehensive literature review, starting with the significance of music in marketing. This will be followed by a short look at the history of AI music generation tools and a comparison of different software architectures. I will also go over a few examples of how generative AI is already being used for marketing purposes today. After the literature review, I will present the research design and display the results and analysis of the data obtained through our experiments. Lastly, I will discuss the broader implications of the findings, address potential limitations and suggest future research questions in a future research questions table.

2 Related Work

2.1 Music in Marketing

Brands carefully form their image to resonate with their target audience. To achieve this, every element, from prices, quality and design choices, are carefully considered. Details like color schemes and font selections are carefully chosen to underline the brand's identity. Modern companies focus not just on selling individual products but on creating a cohesive brand experience (Neese, 2015). Therefore, music selection also plays a crucial role in this process. The right soundtrack can underline and enhance what the brand represents, further deepening its connection with consumers (Neese, 2015).

2.1.1 The role of music in advertising

Using music to enhance your marketing efforts is by no means a new idea. In the article (Tom, 1990), music is described as a powerful tool to evoke memories. The paper found that music can significantly help recall advertised products. Interestingly, popular radio hits in their original versions had the lowest recall score, followed by parody songs. Music specifically composed for the advertisement achieved the highest recall rates. Other early studies also examined the influence of music on consumer behavior, showing that different types of music can affect the time spent in a store and the quantity purchased by customers (Keller, 1984). And since music in marketing has proven to be highly effective (Neese, 2015), many studies about its various effects are being conducted to this day.

Before we further look at how music influences consumer behavior, it is important to first consider where and how modern customers listen to music. Two primary distinctions can be made: music played inside physical retail stores or restaurants and music used in advertisements, whether online or on TV. For many decades, most advertisements were shown on TV, but with the recent decline in watch time, online platforms have taken over. On average, internet users now spend roughly 30% more time on social media than watching TV (McKay, 2023). Naturally global spending on social media advertising has significantly increased and in 2023 it surpassed 207 billion USD (McKay, 2023). One of the key advantages of social media advertising is the ability to get nearly instant customer engagement and feedback. This is particularly valuable when testing campaigns featuring AI-generated music, as the fast feedback allows quick adjustments to an advertisement if necessary.

Ideally both areas of marketing music exposure (in-store and in advertisements) should be used together as suggested by the "Music affect model" by (Kerr & Das, 2014) (Figure 1). The brands advertisements (Online or TV) can positively influence consumer behavior, from the initial exposure to the advertisement to the decision to visit the store. Then the right in-store music can enhance customer behavior during the visit, impact shopping outcomes and boost purchase intentions.

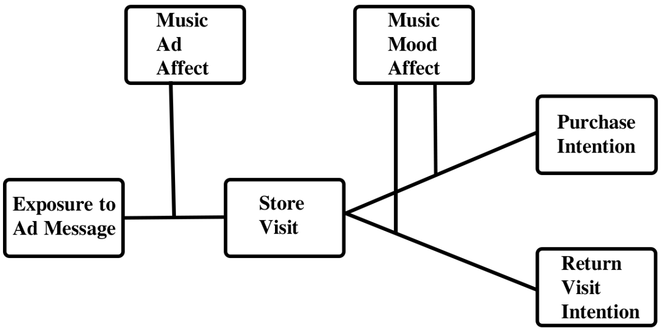

Figure 1: Music affect model (Kerr & Das, 2014)

2.1.2 Psychological and emotional impact of music on consumers

So why is marketing with music so effective? One reason is that humas cannot turn of their hearing ability. "People live in symbiosis with sound and determine dimensions in life through it" (Hultén et al., 2009). Furthermore, humans have a remarkable ability to recall sounds from the past. Music associated with a particular time period can evoke powerful emotions, allowing people to relive memories and, for example, feel youthful again (Hultén et al., 2009). Through cost-effective and rapid music generation AI introduces the capability of creating hyper-personalized music tailored to the demographic profile of individual viewers of advertisements. Another key reason why marketing with music is so effective is the ability of music to influence people's mood. Moods being understood as more muted states of feelings than emotions (Gardner, 1985). And in turn, moods can influence consumer behavior. Many customers tend to make purchases not solely based on a products facts and features, but based on the feelings they experience when thinking of a product (Pham, 1998). This is referred to as the "How do I feel about it?" or *HDIF* heuristic, where positive feelings toward a product make it more appealing and increase the likelihood of purchase. Additionally, a positive mood can help with brand name recognition (Gardner, 1985). Selecting the right song for your marketing efforts can therefore lead to numerous positive outcomes, influencing consumer behavior and brand recall over time.

It has been observed that different types of music can influence different peoples moods in similar ways (Rosenfeld, 1985). Two key factors in any musical piece are tempo and pitch. High-tempo songs, typically classified at 94 BPM or higher, tend to make listeners feel more energized and joyful. On the other hand, lower-tempo songs, around 72 BPM or lower, have a calming effect. This is likely because it aligns with the average resting heart rate of around 72 BPM. Additionally, songs with a higher pitch are generally perceived as happier, whereas lower pitched songs tend to evoke a feeling of sadness (Bruner, 1990). These are just some factors to consider when selecting the right music. Whether for advertisements or in store environments, the right songs can evoke the desired emotional response from customers.

Music plays an important role in marketing, and with an increasing internet usage, its importance is going to grow even further. In a competitive market, music can be a key differentiator, that helps brands in their segmentation and positioning strategy. This enables them to place themselves in a unique market position and reach the right audience. AI music has the ability to create hyper-personalized music tailored to specific consumer groups, or even individual customers, that can provide the competitive edge needed to stand out in today's market.

2.2 Music Generation using AI

In this segment, we will take a brief look at the early attempts and the history of computer-generated music as well as discuss the software architectures and approaches behind different music generation tools. I will also introduce the two state-of-the-art tools that are accessible to everyone and that I will be using for our research in the next chapter.

2.2.1 The History of AI generated Music

The "*Illiac Suite for String Quartet*" is widely regarded as the first song created by a computer (Gage, 2021). In 1957, american composer Lejaren Hiller and mathematician Leonard Isaacson used the *ILLIAC I*, a computer weighing five tons, to conduct experiments in computer-assisted composition. Of course, the methods they used were still very different from the deep learning algorithms we use on today. Hiller and Isaacson used stochastic processes and rule-based algorithms to accept or reject randomly generated rhythms and pitches (Sandred et al., 2009). However, these rules were set by a human, meaning the composer still had a lot of control over the final output. As a result, the system was very limited in its ability to adapt to different musical styles beyond the rules it was programmed with. Nevertheless, the output was a qualitative piece of music created by a computer and therefore bypassing the traditional composition process. This marked the first example of algorithmic thinking in music, which has become more common since (Gage, 2021).

Three decades later in 1985 David Cope developed a computer program, which was initially intended to help him finish a commission. The system developed by Cope is known as "*Experiments in musical intelligence*" or in short "*EMI*". *EMI* uses a database of songs as input data. It then also uses a rule-based system but focusses on the recombination of musical elements from the database of pre-existing works (Silva, 2003). *EMI* does not rely on randomness in the way the creation of the *Illiac Suite* did, it rather analyzes pieces of music for their structural patterns (melodic, harmonic, and rhythmic) and then recombines these patterns in a logical and stylistically coherent way. *EMI* was developed later with the goal of mimicking musical styles and creating new compositions in the style of specific composers.

2.2.2 Current technology and methods

In the 2010s the emergence of deep learning technologies greatly accelerated the possibilities with AI music generation (Du et al., 2016). Various architectures have contributed to advance the field of AI music. In this section, we will explore some of the recent architectures and discuss their strengths and weaknesses. While the technical details behind these tools are not the main focus of this paper, we will briefly address them for the sake of completeness. Most of the information is taken from these two papers, (Civit et al., 2022) and (Briot, 2020). Please refer to them for a more detailed explanation.

- **Evolutionary algorithms**

  Evolutionary algorithms are modelled after Darwin's theory of evolution. These algorithms start with small musical fragments and modify them through mutation and crossover functions to create new melodies.

  Evolutionary algorithms use principles of music theory as rules. This makes sure that generated melodies fit into the desired output. This method relies on gradual improvement through iteration and is often used together with other methods.

- **Feedforward Networks**

  Feedforward Networks (FF) are a rather simple architecture that serve as a foundation for more complex approaches. As the name suggests, FF networks are unidirectional, which means information is only passed on in one direction through the network, without any loops or recursions.

- **Recurrent Neural Networks**

  Recurrent neural networks (RNNs) on the other hand, are not unidirectional and have also become essential for many music generation architectures. RNNs process sequences by using internal memory to retain information from previous steps, making them particularly suitable for generating musical sequences. The most popular variant is the LSTM (Long Short-Term Memory) networks. It can capture long-term dependencies, allowing it to generate high quality compositions over time.

- **Generative Adversarial Networks**

  Generative Adversarial Networks (GANs) consist of two competing networks: a generator and a discriminator. The generator creates an output, in our case a song, that the discriminator then takes as input to decide how realistic it is. This creates a feedback loop in which the generator improves its ability to create music that the discriminator cannot easily distinguish from human made compositions. GANs are often combined with other architectures like feedforward or recurrent networks.

- **Variational Autoencoder**

  Variational Autoencoder (VAE) maps input music into a latent space, capturing essential features while leaving out unnecessary details. The decoder part then uses a distribution to map each point back to the input space which generates new pieces. VAE's are particularly effective for exploring creative variations within musical data by modifying the latent space. VAEs are not only used for composition but also work well audio compression.

- **Transformer Model**

  In recent years, Transformer Networks have become more popular due to their ability to model long-term dependencies in sequential data, such as music. Unlike RNNs, which process data sequentially, transformers use attention mechanisms to consider all parts of a sequence at once. This makes them particularly useful for generating complex compositions.

- **Latent Diffusion Model**

  The newest addition to the list of music generation architectures is latent diffusion. The system uses a VAE, which compresses raw audio into a lower-dimensional latent space. Then it uses a diffusion process to refine and progressively generate audio content. The diffusion model operates iteratively, adding small modifications to the latent representation until the desired audio output is achieved (Evans et al., 2024). The use of latent diffusion makes the system computationally efficient, which is beneficial for generating long-form audio at high quality.

Together, these architectures demonstrate the fast evolution of AI for music generation. As these technologies continue to develop, AI is going to become an even more powerful tool in the world of music creation.

2.2.3 Suno AI & StableAudio

In the final part of this chapter, we will explore the state-of-the-art tools which will be used for our research in the following chapters. The two tools we will focus on are Suno AI and StableAdio. They both launched in late 2023, which makes them among the first, easy-to-use online platforms that allowed users to create full length songs from a single text prompt.

As of September 2024, both music generation tools offer a similar free plan and pricing strategy. The free plan limits the number of songs that can be generated within a certain period. The paid plans, ranging from 10 Euro to 90 Euro per month for StableAudio's max tier, increase the number of songs that can be generated. They also unlock some additional features such as commercial use, priority in the generation queue for a faster song creation process and more simultaneous generation jobs. Furthermore, Suno and StableAudio allow you to upload audio files as reference. However, none of the mentioned tools have options for further customizing or modifying the generated songs (StableAudio.com, 2024; Suno.com, 2024).

StableAudio 2.0, which is Stability.ai's newest version claims to have been "exclusively trained on a licensed dataset from the *AudioSparx* music library, honoring opt-out requests and ensuring fair compensation for creators" (Stability.ai, 2024). Suno, on the other hand, has kept their exact training data a secret. This raises copyright issues which has already led to a law suit by the Recording Industry Association of America (RIAA) (Rogès, 2024).

What is known about their models, however, is that they not only use songs but also voice recordings to train their AI. More specifically Suno mainly utilizes a transformer networks architecture to generate music (NoPriors-Podcast, 2024). StableAudio, on the other hand, uses a latent diffusion model. Its architecture is made up of a autoencoder that compresses the raw audio data and a diffusion transformer (DiT) that "refines random noise into structured data incrementally, identifying intricate patterns and relationships" (Stability.ai, 2024).

2.3 AI-generated Music in Marketing

In this chapter we will take a look at how AI is already being used in marketing today. There have already been many successful advertisement campaigns using AI. For example, in 2023 Coca-Cola held an art contest in which they invited digital artists to create Coca-Cola themed artworks. This was done with the help of a custom-built image generation platform based on OpenAI's GPT-4 and Dall-E (Coca-Cola, 2023). For Nike's 50^{th} anniversary their campaign "Never Done Evolving" included two digital models of the tennis star Serena Williams playing each other. The innovative part was, that each model was trained with real data gathered from her real matches using AI. The final was then broadcasted on YouTube with 1.7 millions viewers, a significant increase of views compared to Nikes other content (WPP, 2022). Or in 2019 JPMorgan Chase partnered with Persado, an AI Text tool which focusses on generating texts for marketing purposes, to rewrite their ad copy. This increased JPMorgan Chase's CTR by 450% (Persado, 2019). These were just a few examples of how AI is already being used in marketing today.

But what about advertisement campaigns utilizing AI-generated music specifically? In early 2024 the American sea food chain Red Lobster created a playlist on YouTube with 30 songs about their highly popular Cheddar Bay Biscuits. All the songs in this advertisement campaign were AI generated and covered a wide variety of genres (Nelson, 2024). Several of the songs have become some of the most watched videos on the channel, with the majority of comments praising the biscuits or the AI-generated music for their quality and innovativeness. Overall, the advertisement received a highly positive response from its audience, leaving a positive impact. With modern AI music tools such as the ones discussed in the previous chapter, it is safe to assume that the advertisement campaign was inexpensive yet, judging by the consumer response, highly effective.

In my research I was unable to find more examples of established brands using AI-generated music in advertisements. This might be due to easily accessible music generation tools still being very new in their availability to the public. There is also the possibility that AI-generated music has been used in advertisements discreetly, as the general public still has a bias against AI music, and publicly acknowledging its use might attract unwanted criticism (Zenieris, 2023). Furthermore, some studies suggest that AI-generated music is now often indistinguishable from human composed music (Highams & Olszewska, 2023). This means there is a possibility that AI music is already in wider use than we realize. What is known, however, is that content creators are already using AI-generated music to produce content on platforms like YouTube, Facebook and TikTok. This allows them to avoid copyright issues and generate revenue more freely (Soundful, 2024).

The adoption of easy to use off the shelf AI music tools is still in its early phase. The examples presented have demonstrated the potential of AI being used in marketing campaigns. To further assess the effectiveness of AI-generated music we will gather and analyze data from real-world studies in the next chapter.

2.4 Hypotheses

Building on the findings of this chapter, this study aims to bridge the gap between existing research on AI-generated music and its practical applications for marketing. Given the limited research on how AI-generated music might perform against traditional compositions in digital advertisements, I came up with four hypotheses:

- **H1**: *Casual music listeners will not significantly differentiate between AI-generated music and human-composed music in terms of overall quality.*
- **H2**: *The choice of the AI models architecture will impact the overall satisfaction of AI-generated music by casual listeners.*
- **H3**: *A casual listeners attitude towards AI technology will positively correlate with their ratings of AI-generated music for marketing purposes.*

- **H4**: *AI-generated music will achieve a higher click-through rate (CTR) than royalty-free music when used in identical advertisements on social media.*

3 Empirical Investigation

3.1 Research Design

Two studies were conducted to obtain empirical data to answer the question if AI generated music can be as effective, if not more effective than traditionally composed music in advertising. Through rejecting or failing to reject our previously outlined hypotheses the research questions, stated in the following table (Table 1), will be answered.

Table 1: Overview of the two studies

	Study 1	**Study 2**
Research Question	How do casual music listeners perceive AI-generated music for marketing purposes compared to traditionally produced music, and does the choice of AI model architecture influence these perceptions?	Can AI-generated music outperform royalty-free music in digital advertising by achieving a higher click-through rate when used in identical ads on social media platforms?
Dependent Variables	Overall, Creativity, Naturalness, Melodiousness, Correctness (Chu et al., 2022) Prompt Following	CTR (Click-through rate)
Setup	Online Survey (Lab setting) • 2 AI-generated songs (Suno AI based on transformer models and StableAudio based on transformer diffusion models) • 1 song made by a human producer • 41 participants	Online Advertisement (Field experiment, A/B Testing) • 1 ad with AI generated song (Suno AI) • 1 identical ad with Royalty free music • Facebook Advertisement: 10 days for 200€ (10€ per day per advertisement) • 52680 total impressions

3.2 Online Survey (Lab Setting)

The initial study is made up of a two-part survey. It begins with collecting general information about the participant, such as age, gender and their general attitude towards AI technology and AI-generated music. All questions in the first and second part of the survey, except the questions about age and gender, are answered on a 5-point Likert scale, where 1 indicates strong disagreement, and 5 strong agreement with the presented statements.

In the second half of the survey the respondent listens to three song snippets. Two songs are AI-generated and one was made by a human producer with an expertise in commercial music composition. For the AI-generated songs, I utilized Suno AI, which primarily employs transformer models, and StableAudio, which is based on diffusion models. By comparing these two different software architectures to a human producer, the goal is to determine which approach performs best and whether the choice of model architecture significantly impacts the perceived quality of the music. The participants were not informed about whether a song was AI-generated or not. In fact, no indication was given regarding the origin of the songs. This approach was intended to prevent listeners from searching for signs of AI involvement, which could have distracted them from providing unbiased ratings.

To make the comparison as fair as possible, the exact same prompt was given to both AI tools as well as the human producer with no further instructions or communication, except that the song must be an instrumental. The prompt provided was the following: “Happy, upbeat, summer hip-hop beat for a drink commercial”. This prompt was intentionally formulated in a way that includes an emotion (happy) and a musical genre (Hip-Hop), ensuring that all the generated songs would follow a similar direction. Including the context of a drink commercial was also crucial, as this would of course be known in a typical advertisement campaign briefing. Additionally, I introduced a subtle contradiction by combining the description “upbeat” with “hip-hop beat”, two elements that can have contrasting sonic qualities. This added some room for creative interpretation. For each prompt Suno AI automatically generates two songs. I selected the one that sounded best to me, as this is how someone would realistically choose AI-generated music for an advertisement.

Each snippet is exactly 30 seconds long. This gives the listener enough time to get a good idea of the song without risking listening fatigue. For all three songs the first 30 seconds were chosen. After each song snipped there are six questions to assess the participants impressions. The questions are derived from (Chu et al., 2022), but instead of the nine criteria outlined in that paper I have condensed it down to the five most relevant plus a sixth criteria which assesses how closely the song aligns with the given prompt. The six criteria are:

- **Overall**: What is your overall satisfaction with the song?
- **Creativity**: Is the song novel, valuable, and original?
- **Naturalness**: Does the piece sound like an expressive human performance?
- **Melodiousness**: How musical and harmonious is the song?
- **Correctness**: Does the song play with any technical glitches?
- **Prompt Following**: How well does the song fit the given prompt?

Consistent with the approach of (Chu et al., 2022) the survey targeted casual music listeners without any formal background in music. This was done to get the most authentic and natural ratings, simulating a real-world scenario for advertisements. A clear definition for every criteria as well as the prompt, used to create the songs, was provided.

3.3 Online Advertisement (Field Experiment)

The second part of the research is a field experiment, conducted by running paid advertisements on social media platforms. I created two identical 15 second animated clips that advertise *Imparat*[1] paint for your home. I partnered with IMparat Farbwerk GmbH & Co KG to obtain the funding for the real-world A/B test and to help them kick of their social media advertisement campaign. I added music generated by Suno AI to one video and a royalty-free song from Pixabay to the other. I chose Suno AI as my AI song generator because the results of my online survey indicated early on that it would outperform the song generated by the diffusion model of StableAudio. To make it as fair as possible I created a simple prompt that could also be used as a search term in the Pixabay audio library. The prompt I used was "Chill melodic lofi beat". I again chose the song from the two generated by Suno AI that sounded best to me. A similar approach was used when selecting the royalty free song. Within the first page of the search results of my given prompt I selected the song I found most suitable.

The advertisements were then published through Meta's Ad Center, which showed them on Facebook and Instagram. I chose Meta because it offers an uncomplicated way to publish advertisements with a low daily budget. Additionally, it offers insights into the advertisement's performance providing crucial data such as total impressions and link clicks, which we need to determine the CTR. Both advertisements were uploaded at the same time, with a runtime of 10 days (27.10.2024 – 05.11.2024) and a daily budget of 10 Euro. As mentioned by (Hartmann et al., 2024) this type of real world A/B test aims "to increase the ecological validity of our findings".

[1] Imparat is a paint company based in Hamburg, Germany

4 Results

4.1 Participants

For the online survey we had 41 participants of which 55.6% identified as female, 37.2% as male and 7% as diverse. With around 60%, most of the respondents were between 21 – 30 years old. 18.5% were 46 – 60 years old with the rest being relatively evenly distributed among the remaining age groups. All the participants are based in Germany.

Our field experiment generated a total of 52680 impressions, with approximately 60% of the reached accounts being male. The age distribution was relatively balanced across all groups between 25 and 64 years, accounting for around 22% each. The remaining 12% of the profiles reached were in the age range of 65+. The advertisement campaign targeted geolocations where IMparat Farbwerk GmbH & Co KG has a physical presence, resulting in all reached accounts being based in Germany as well.

4.2 Results – Online Survey

Overall, our participants have a positive attitude towards AI technology. With an average of 3.49 on a 5-point Likert scale where 1 indicated a negative, and 5 a positive view on AI technology. At first this might seem suspiciously high when considering that according to (Schneider, 2021) around 40% of Germans are skeptical towards AI technology. Taking into account the younger demographic of our survey, the higher acceptance rate makes sense since only 19% of the AI skeptics in Germany are between the ages of 18 and 34. This age group makes up 24% of the total population of Germany (Schneider, 2021). With an average of 3.39 the origin of a song also seems to be important to our respondents. The question if AI songs are still considered art was more divisive. With an average score of 2.61, participants are roughly balanced in their disagreement and agreement with that statement.

Which song performed the best? To answer this question, we took the average of all six song categories and plotted them against each other as seen in Figure 2. Song 1, which was generated by Suno AI achieved the highest score in the *Overall* category with an average of 3.42. Followed by the human composed song with 3.27 and the song generated by StableAudio with a score of 2.73. For the category *Creativity*, *Naturalness* and *Correctness* the human-made song scored the highest means with 3.54, 3.15 and 4.32. Song 1 got the highest average score for *Melodiousness* and *Prompt following* with 3.98 and 4.05.

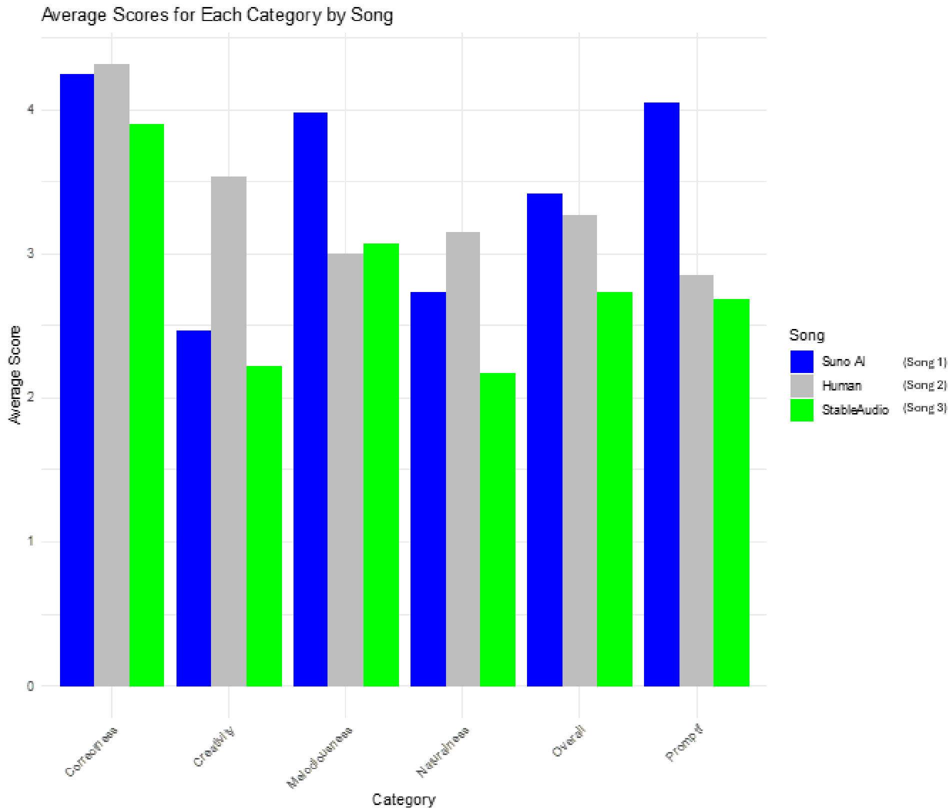

Figure 2: Bar chart of the means of each song category

To investigate if the differences in means are significant, I ran an OLS regression on all six song related categories and used Song 2 from my survey, which was the human-made song, as a baseline. The results are displayed in Table 2.

Table 2: OLS regression results on the impression of AI music compared to human made music in an advertisement context

Human made song vs AI generated songs						
	Dependent variable:					
	Overall	**Creativity**	**Naturalness**	**Melodiousness**	**Correctness**	**Promptfollowing**
	(1)	(2)	(3)	(4)	(5)	(6)
Suno AI	0.146	-1.073^{***}	-0.415	0.976^{***}	-0.073	1.195^{***}
	(0.261)	(0.248)	(0.274)	(0.228)	(0.235)	(0.233)
StableAudio	-0.537^{**}	-1.317^{***}	-0.976^{***}	0.073	-0.415^{*}	-0.171
	(0.261)	(0.248)	(0.274)	(0.228)	(0.235)	(0.233)
Constant	3.268^{***}	3.537^{***}	3.146^{***}	3.000^{***}	4.317^{***}	2.854^{***}
	(0.185)	(0.175)	(0.194)	(0.161)	(0.166)	(0.165)
Observations	123	123	123	123	123	123
Within R^2	0.0437	0.1969	0.081	0.1453	0.0125	0.2408
Observations	123	123	123	123	123	123
R^2	0.059	0.210	0.096	0.159	0.029	0.253
Adjusted R^2	0.044	0.197	0.081	0.145	0.012	0.241

Note: *p<0.1; **p<0.05; ***p<0.01

Most notably in the category *Creativity* both Suno AI ($\beta_{Creativity} = -1.073$, $p < 0.01$) and StableAudio ($\beta_{Creativity} = -1.317$, $p < 0.01$) had highly significantly worse outcomes compared to the human-made baseline. Across all six categories StableAudio had significantly lower values in four of them. Besides the previously mentioned creativity score, it had a significantly lower score for *Overall* ($\beta_{Overall} = -0.537$, $p < 0.05$), a highly significantly lower score for *Naturalness* ($\beta_{Naturalness} = -0.976$, $p < 0.01$) and a marginally significantly lower score for *Correctness* ($\beta_{Correctness} = -0.415$, $p < 0.1$). On the contrary, Suno AI did not perform significantly worse in any category, except for the already mentioned *Creativity* attribute. It was able to significantly outperform the human-made song in two categories: *Melodiousness* ($\beta_{Melodiousness} = 0.976$, $p < 0.01$) and *Prompt Following* ($\beta_{Promptfollowing} = 1.195$, $p < 0.01$). It is important to note that, although the differences in values are statistically significant, the real-world differences may be minimal. Since the results are based on a 5-point Likert scale, some of the observed values are only slightly above or below the baseline when examining the actual scores.

Combining all the means for each song, Song 1, which was generated using Suno AI, achieved the highest score of 20.88. Closely followed by the human made song with 20.12. StableAudio had the lowest aggregate score with 16.78.

To examine the influence of selected variables on the *Overall* metric for each song, I conducted regression analyses (Table 3). In the first model, I used only the participants attitudes towards AI as independent variables: whether they like AI, whether the origin of a song is important to them, and whether they consider AI-generated music to be art. In the second model, I also included the song metrics: Creativity, *Melodiousness*, *Correctness*, *Naturalness*, and *Prompt Following* as independent variables.

Table 3: Regression on the *Overall* metric of each song

		Suno AI		**Human song**		**StableAudio**	
	Variable	ovReg1	ovReg11	ovReg2	ovReg22	ovReg3	ovReg33
1	Like_AI	−0.0231 (0.85129)	0.22398 (0.12032)	−0.07057 (0.72902)	−0.01708 (0.8837)	0.1528 (0.25881)	0.23643 (**0.04345**)
2	Song_Origin	0.03884 (0.76255)	−0.02569 (0.86066)	0.29121 (0.17559)	0.05589 (0.67965)	−0.00647 (0.96315)	−0.05557 (0.62501)
3	AI_is_Art	0.40536 (**0.00173**)	0.21116 (0.19765)	0.01815 (0.92759)	−0.24191 (**0.04661**)	0.42264 (**0.00257**)	0.07538 (0.51923)
4	Creativity		0.24313 (0.38425)		0.01366 (0.95699)		0.25075 (0.15242)
5	Naturalness		0.1184 (0.56624)		0.39057 (**0.0419**)		0.15019 (0.41823)
6	Melodiousness		0.27426 (0.25528)		0.68432 (**0.00097**)		0.42172 (**0.0085**)
7	Correctness		−0.0595 (0.7187)		−0.21047 (0.14952)		−0.02534 (0.84768)
8	Promptf		−0.17305 (0.47609)		0.23489 (**0.06585**)		0.14736 (0.32751)

The table shows that a participant's general attitude toward AI technology only had a significant positive effect on the overall perception of the song generated by StableAudio when the regression included additional song metrics ($\beta_{Like\_AI} = 0.236$, $p < 0.05$). The importance participants placed on the origin of a song did not significantly affect their overall perception of any song. Agreeing strongly with the statement that "AI music still counts as art" appears to have a positive impact on the *Overall* metric for both AI-generated songs: Suno AI ($\beta_{AI\_is\_Art} = 0.405$, $p < 0.01$) and StableAudio ($\beta_{AI\_is\_Art} = 0.423$, $p < 0.01$). For the human generated song, however, this belief had a significantly negative effect when all independent variables were included in the regression ($\beta_{AI\_is\_Art} = -0.242$, $p < 0.05$). Among all song-related metrics, *Melodiousness* had the highest positive effect on the overall perception of the song. For two out of the three songs, it had a highly significant impact: the human-made song ($\beta_{Melodiousness} = 0.684$, $p < 0.01$) and the StableAudio song ($\beta_{Melodiousness} = 0.422$, $p < 0.01$). This aligns with the findings by (Chu et al., 2022), where *Melodiousness* also had the greatest impact on a songs overall impression.

4.3 Results – Online Advertisement

Analyzing the data from my social media ad campaign was much simpler. The advertisement video with the AI-generated music by Suno AI had a total of 23055 impression and 206 link-clicks after 10 days. The advertisement with the royalty-free music had 29625 impressions with 246 link-clicks during the same time period. This leads to a CTR (click-through-rate) of 0.894% for the advertisement with the AI music and 0.830% for the advertisement with the royalty-free music. To investigate the significance of the click-through rates (CTR) between the campaigns, a chi-squared test was conducted (Table 4). The null hypothesis for this test assumes that the CTR's for both campaigns are statistically identical, with any observed differences being due to random variation.

The Chi-squared test concluded that the difference in CTR between the two ads is not significant. This is indicated by the relatively low chi-squared value (0.5356) in line 5 of Table 4 and the p-value (0.4643) in line 7, which is above the typical threshold of 0.05. We therefore cannot reject the null hypothesis and conclude that neither the advertisement with the AI or the royalty free music performed significantly better or worse than the other.

Table 4: Chi-squared test results for ad CTR comparison

	Metric	Suno_AI	Royalty_Free	Test_Results
1	Click–through Rate (CTR)	0.89%	0.83%	
2	Observed Clicks	206	246	
3	Total Impressions	23055	29625	
4	Difference in CTR			0.06%
5	Chi–squared Value			0.5356
6	Degrees of Freedom			1
7	p–value			0.4643
8	95% Confidence Interval (Lower)			−0.10%
9	95% Confidence Interval (Upper)			0.23%

4.4 Analysis of Findings for the Research Questions & Hypotheses

After analyzing the data, we can now answer the research questions outlined in Table 1 and evaluate the hypotheses presented in chapter 2.4.. The results do not support H1, which means that casual music listeners do significantly differentiate between AI-generated and human produced music in terms of perceived overall quality. As shown in Table 2, the song generated by Suno AI scored significantly higher than the human composed song in two out of six categories: *Melodiousness* and *Prompt Following*. Table 4 revealed that *Melodiousness* has the largest impact on the *Overall* metric. Although Suno AI's song achieved a numerically higher mean in the *Overall* category than the human-composed song, this difference was not statistically significant. However, in advertising contexts, the *Prompt Following* metric is crucial, as it indicates how well the music aligns with specific instructions. Notably, Suno AI's song only scored significantly lower than the human song in the *Creativity* category. On the contrary, the song created by StableAudio scored significantly lower than the human composed song in four out of the six categories. Only *Melodiousness* showed a numerically higher score. Since one AI-generated song performed better than the human composed song and the other performed worse, we must reject H1, as there is clear evidence that listeners differentiate the perceived overall quality of AI-generated and human composed music. These findings lead us right into Hypothesis 2, which suggests that the choice of AI model affects how people judge the quality of music. Since the song generated by Suno AI significantly outperformed the song made with StableAudio, we fail to reject H2.

Our third hypothesis (H3) suggests that a positive attitude towards AI technology correlates with higher ratings for AI-generated songs in a marketing context. Table 3 shows the results from four regressions conducted on the two AI songs. Of these, three show a significant positive effect in at least one of the three categories related to AI technology attitude *(Like_AI, Song_Origin* and *AI_is_Art)*. The category *AI_is_Art* had a significant positive effect on both AI songs but only for the regressions where only AI related variables were included. Additionally, for the AI song made with StableAudio, the category *Like_AI* had a positive effect on the song's overall score. This time only in the regression that included all other variables. Interestingly, for the human composed song, *AI_is_Art* had a negative effect on the *Overall* rating. All in all, the data delivers some indicators supporting H3, but the data is not entirely consistent, and the results should be interpreted with this in mind.

The fourth hypothesis proposed that AI-generated music, when used in an otherwise identical social media advertisement, would achieve a higher click-through rate (CTR) than human-made, royalty-free music. As shown in Table 4, the advertisement with the music from Suno AI did have a numerically higher CTR than the advertisement with royalty-free music (0.89% vs. 0.83%). However, the chi-squared test revealed that this difference is not statistically significant. We can therefore reject the H4 hypothesis. These findings provide clear answers to the research questions presented in Table 1, contributing to our understanding of the potential of AI-generated music in marketing.

5 Discussion

5.1 Summary

High-quality AI-generated music is not just a potential technology of the future, but a reality today (Lin & Chen, 2024). Some studies suggest that AI-generated music is already indistinguishable from human-made compositions (Chu et al., 2022; Highams & Olszewska, 2023). However, other studies also show a persisting bias against AI music (Zenieris, 2023). This is an obstacle AI-generated art in general still needs to overcome. Other than its quality, there are other compelling reasons for using AI music, such as significant advantages in production time and cost compared to human-made music.

In our survey, the AI-generated songs took less than two minutes to create, and the cost was effectively zero, as we used a free plan for non-commercial purposes. In contrast, the song created by a human producer took approximately three days to make, not because it required that much time to be produced, but because of limited human availability. While, due to a personal connection, the producer volunteered for this project, he provided a hypothetical invoice of 200 Euro, based on four hours of work at a standard rate of 50 Euro per hour. Given this producer's relatively young age and freelance career, this cost estimate can be considered conservative.

For our field experiment, the costs were slightly different. Because the AI-generated music was used in a commercial setting it required a paid subscription to Suno AI. I chose the lowest tier, which cost 10 Euro per month. This would have allowed me to generate up to 500 commercially usable songs. Since I only needed one song, I calculated the effective cost to be 10 Euro. Although the royalty-free song used in the study was free, finding a suitable royalty-free song that met all criteria was more challenging than I had anticipated, with limited options available.

The data from our questionnaire indicates that a human producer may not always produce a song that perfectly aligns with a given description. In the *Prompt Following* category, Suno AI achieved a significantly higher mean score than the human produced song. Even StableAudio, which performed significantly worse overall, only showed a numerically lower score in this category. This suggests that while human producers bring a unique style, influenced by personal taste and experience, this can sometimes get in the way of a precisely chosen description. On the other hand, when a client is not sure what exactly they are looking for, this can be a great advantage. When the desired attributes are clearly defined, however, AI can generate a song that meets these specifications with equal, if not greater, accuracy.

Additionally, AI enables rapid iterations. If the generated music does not fully meet expectations, slight adjustments to the prompt can produce a new version within minutes. This capability introduces new possibilities for advertising. Multiple versions or styles of a song could be generated quickly and at a low cost. Advertisers could then conduct real-world A/B tests and evaluate which version performs best with their target audience, always choosing the most effective option (Schwartz et al., 2017). This rapid feedback loop, directly involving the target audience, can help increase effectiveness and engagement (Fletcher, 2024).

The already discussed low cost, rapid creation, and high flexibility of AI-generated music open up possibilities for hyper-personalized advertising, a method that has been shown to be more effective than traditional advertising (Monem, 2021). With high-quality, user-friendly AI music tools, it is possible that future advertisements could feature music customized for individual user preferences. These song customizations could be based on data such as age, location, language, and browsing behavior. Such a level of personalization would be impractical, if not impossible, without the efficiency of AI tools.

There are, however, also potential downsides to using AI-generated music. On a technical level AI is currently limited in its ability to generate highly specific or niche requests, that require a level of creativity which currently only humans have. This limitation was supported by the results of Study 1, where the *Creativity* category was the only one receiving significantly lower ratings for both AI models compared to the human composed song. Although we lack data on whether participants recognized the AI-generated songs, and thus rated them lower in creativity, it is possible.

Moreover, there remains a general bias against AI-generated music (Zenieris, 2023), which could be a risks for companies using this technology. If audiences perceive AI-generated music negatively, it could impact the brands image and reduce the effectiveness of their marketing campaigns. This bias is likely due to ethical concerns, such as copyright issues related to the training data used for AI models. There is also the issue that AI-produced music could closely resemble works by known artists without paying them royalties. Addressing these concerns will be essential to achieving broader acceptance and integration of AI-generated music in commercial settings.

5.2 Implications for Marketing

AI-generated music has emerged as a valuable tool in the marketing industry, offering both advantages and disadvantages. For smaller companies with limited budgets, AI-generated music can help level the playing field (Acar & Gvirtz, 2024) by providing high-quality compositions at a fraction of the cost of a traditionally licensed song. This is particularly beneficial in competitive markets where established corporations have much bigger budgets for their marketing strategies. The data from our second study highlights that AI-generated music, produced using readily available tools, has reached a high level of sophistication. This allows it to be seamlessly integrated as background music, enhancing other elements of the marketing mix.

On the other hand, the current state of AI technology has its limitations when producing music that aims to have a lasting cultural or emotional impact. AI lacks the true creativity required to compose iconic songs that remain memorable and elevate a brand's identity. As of six months after its launch, Suno AI had attracted over 12 million users (Tencer, 2024). Nevertheless, only a single fully AI-generated song has made it into the German music charts[2] (Kramer, 2024), and not a single AI song has achieved this in the U.S. This suggests that while AI is a powerful tool for specific applications, it still needs to demonstrate its potential for creating hit songs capable of deeply engaging audiences.

5.3 Limitations of the study and suggestions for future research

First, I will address the technical limitations of my research. The questionnaire included 41 participants, with over 65% being 30 years old or younger. This demographic distribution could have introduced a sample bias. The results could be influenced disproportionately by the majority of younger participants. Additionally, the sample size prevented meaningful analysis of data across different age groups, as there would not be enough data points within each

[2] In August of 2024 the song "Verknallt in einen Talahon" by Butterbro debuted in the top 50 of the German charts. The song, except for the lyrics, was entirely AI generated using Udio AI

Table 5: Future research question table

Area of focus	Research question
Demographic influence	How do different age groups perceive AI music?
Platform-Specific effectiveness	How does AI generated music perform in advertisement on platforms such as YouTube and TikTok?
AI vs professional music productions	How does AI-generated music compare to tracks produced by high-budget professional compositions?
Long-Term impact	Can AI-generated music improve long-term marketing outcomes, such as brand recall and customer loyalty?
Consumer bias and perception	How does consumer bias against AI-generated music impact its effectiveness in marketing campaigns?
Hyper-Personalization potential	How effective is hyper-personalized AI-generated music in marketing?
Ad placement context	How does the context (e.g. type of product, target audience) affect the success of AI-generated music?
Legal and ethical considerations	How do copyright and originality issues affect the adoption of AI-generated music in commercial use?
General AI music applications	Beyond marketing, how can AI-generated music be effectively used in industries like film, gaming, and education?

segment for a reliable differentiation. Future research could address this by targeting a larger sample.

Secondly, in our field experiment we were able to obtain a large sample size but were limited to comparing only one AI tool against one royalty-free song. While Suno AI was able to outperform the human composition and the song made by StableAudio in our first study, there are many different AI music tools, each with unique strengths and weaknesses. A broader investigation including multiple AI tools would provide a more comprehensive understanding of the current state of AI-generated music and how it compares to human-made compositions.

Thirdly, according to (Jones, 2021), approximately 85% of Facebook users use the platform without sound. Given that the majority of our impressions were gathered on Facebook, and no data was available whether the advertisements were viewed with or without sound, it is unclear how this might have influenced the evaluation of our advertisements. Future research could make use of other media platforms such as YouTube or TikTok, where music and sound is a core feature of the platform, resulting in less users viewing the advertisements without sound (Jones, 2021).

Additional limitations, outlined in the research by (Hartmann et al., 2024), also apply to this study. Our research focused on the qualitative perception of AI-generated music, measured through categories in Study 1, and the immediate user response in Study 2. Future studies could expand on this by exploring its effectiveness in different contexts and examining additional marketing objectives, such as brand recall or purchase intention. Lastly, we also only compared AI-generated music against a lower-budget freelance producer. Additional studies could investigate how AI music holds up against big budget productions.

These considerations provide a strong foundation for future research. A future research question table is provided with Table 5.

6 Conclusion

The rapid evolution of generative AI has made AI-generated music a promising tool for marketing. This study aimed to explore the effectiveness of AI-generated music in a marketing context. This was done by assessing its perception among casual listeners and investigating the performance in a real-world advertisement campaign. The results reveal both potential and some limitations, suggesting that AI music can be very effective, when used in the right context.

AI-generated music showed its ability to outperform human composed songs in several areas, most notably in the categories *Melodiousness* and *Prompt Following*. With tools such as Suno AI and StableAudio songs could be produced in a fraction of the time and at a significantly lower cost compared to on demand made human music. These attributes make AI-generated music particularly appealing for companies seeking fast, flexible, and budget-friendly solutions for their marketing campaigns. However, the study also highlights limitations of AI-generated music. The data of our study shows that the creative quality of AI-generated music, is still significantly lower than that of human composed music. This finding underlines a fundamental challenge for AI in creative industries: the ability to produce compositions that evoke the same level of passion and originality as human creations. While AI excels in following technical prompts and generating music that fits predefined criteria, it struggles to create truly innovative or iconic tracks that have the potential to contribute to long-term brand identity. Our field experiment suggests that while AI-generated music may not significantly outperform traditional options in terms of CTR, it remains a viable alternative, particularly when budget and time constraints are critical factors.

In the future, advancements in AI technology will likely address many of the current limitations. Developing models that can further enhance creativity and emotional resonance could bridge the gap between AI-generated and human composed music. Additionally, larger, more diverse studies are needed to examine how preference for AI-generated music varies across different demographic groups and cultural contexts. This research serves as an initial step toward understanding the potential of AI music in marketing.

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