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When Music is Made by AI: Effects on Preferences and Willingness to Pay

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When Music is Made by AI: Effects on Preferences and Willingness to Pay*

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January 15, 2026

Abstract

Artificial intelligence (AI) is rapidly reshaping society, including the music industry. Recent advancements in generative AI enable users to create music from text-based prompts, raising questions about public perception and valuation of AI-generated music. We conducted three studies with German-speaking participants (Study 1: N=2000, Study 2: N=425; Study 3: N=1248) to explore awareness, enjoyment, and willingness to pay for AI music. After finding no clear rejection of AI composed music in Study 1, Study 2 varied whether listeners knew the music was AI-generated. Study 3 involved regular listeners of pop and electronic dance music, manipulating song origin (human vs. AI) and disclosure. Results show that listeners generally could not distinguish between AI and human-made songs. When unaware, participants slightly preferred AI music and valued it equally. However, disclosing that AI had been used to create compositions reduced appreciation and willingness to pay. We explore how reactions differ by genre and individual attitudes toward AI and discuss implications for the music industry and for regulatory initiatives.

Keywords: Artificial intelligence, Music, Willingness-to-pay, Ethics of AI

JEL-codes: D12, Z11, O33

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1 Introduction

The creation and monetization of content is the foundation for many digital markets (e.g., music or movies). In the digital age, content is mainly offered by global platforms to consumers (e.g., Spotify). In the music industry, these platforms play a major role; in 2024 69% of global recorded revenues (=US\$20.4 billion of US\$29.6 billion) came from music streaming platforms ([Bundesverband Musikindustrie e.V., 2025](#)). The allocation of the US\$20.4 billion depends on the platforms' remuneration model for content suppliers ([Jensen, 2024](#)). Typically, the platforms claim 30% for their services and the remaining 70% of the subscription and advertising fees (royalty pool) are allocated proportionally to the market share of streams ([Meyn *et al.*, 2023](#)). Thus, the remuneration of content depends on consumers' streaming behavior and the subsequent market share of a song within a month. Besides adding new subscribers, growth in this multibillion dollar business model is realized by the platform if they start participating in the royalty pool by offering their own content. Artists gain if they increase their market share by producing more (high quality) content. Ideally, the new content is produced at very low costs to maximize profits – for example by using AI.

August 1st, 2024 marked the first time that an AI-generated song entered the German charts ([Simpson, 2024](#)), emphasizing the relevance and potential of the use of generative artificial intelligence (AI) and its potential to automate the generation of music. The automation of work has received a lot of attention in economic research and popular discussion alike. While the focus has long been on jobs characterized by routine-tasks which were at higher risk of automation, thereby threatening mostly lower-skilled workers ([Autor *et al.*, 2003](#); [Katz and Murphy, 1992](#)), the development of large language models and artificial intelligence implies that now jobs are affected that were previously considered to require decidedly human skills, like (creative) writing, composing music, or creating art. For example, Google's MusicLM is a text-based AI model that can be used to automatically create original music by learning patterns from vast datasets of existing songs. We expect that AI may improve productivity by individual artists and the music industry more generally, in line with the positive association between AI adoption and productivity observed by [Czarnitzki *et al.* \(2023\)](#).¹ Currently, the regulatory discussion centers on the question how right holders are paid when the AI is trained by their music ([Bundesverband Musikindustrie e.V., 2025](#)). However, given the market share business logic of established remuneration models in the music industry, using AI for music creation is not only very tempting for established artists, but it may encourage new actors to try and participate in the royalty pool.

¹[Czarnitzki *et al.* \(2023\)](#) argue that artificial intelligence can be understood as a “capital asset that enlarges the capacity of a firm to produce more, or more valuable output”, a view that applies very well to what we expect for the music industry.

Using AI to automatically generate music allows platforms, artists, or even external players from the IT business to become content providers and “flood” the platforms with content. Such content must either be sufficiently attractive to consumers to secure a significant market share, or be produced in such large quantities that the overall effect compensates for potentially low individual success rates. Economically, there is no difference between one song generating one million streams and one million songs each generating a single stream. The latter strategy, however, only becomes feasible if music creation can be automated. With the availability of tools that, through simple verbal prompts and without requiring expert knowledge, can generate popular music that is difficult to distinguish from human-made music, it is pertinent to examine their potential economic consequences for the music industry. Our study contributes to better understanding the potential business and welfare implications of AI-use in music generation with a focus on the experiences of music listeners in streaming services. As these are the consumers who may or may not demand and pay for AI-generated music, their preferences are crucial in gauging the implications of these tools for the future development of the music streaming market. We focus on the streaming of music as the dominant way in which music is consumed at the time our studies are conducted. The results of our study can be expected to generalize to other digital markets as well (e.g., book publishing industry).

In light of complex questions regarding attribution of authorship, copyright issues, and economic implications for the business models of creative workers from generative AI (see, e.g., [Fenwick and Jurcys, 2023](#); [Flick and Worrall, 2022](#); [Piskopani *et al.*, 2023](#)), this study offers insights into the preferences of consumers regarding AI-generated music. The preference for or against AI-generated music impacts the “fair” compensation and preservation of human creativity from an ethical perspective. Specifically, automated and widespread uploads of AI-generated songs dilute royalty pools for human artists, making it harder for them to earn a living, which eventually leads to widespread job displacement and a devaluation of the skills of human musicians. Further, the use of AI in the music industry and consumers’ valuation thereof may affect musicians’ self-esteem and the extent to which they experience their jobs as meaningful ([Bankins and Formosa, 2023](#)). Consumers may consider such effects, but only if artists and deployers of music are transparent about the use of AI, can consumers make informed choices. For example, the music by “The Velvet Sundown” is clearly labeled by the creators on Spotify as AI-generated and openly and critically discusses how AI is embedded (Figure 1). Contemporary regulatory initiatives like the EU AI Act take a step toward demanding the labeling of AI use but do not demand that all use of AI be labeled.² Our studies provide empirical insights into the potential economic effects from labeling.

²Specifically, it only makes disclosure requirements only for “image, audio or video content constituting a deep fake” and for generated text, exemptions are made whenever a human oversees and approves

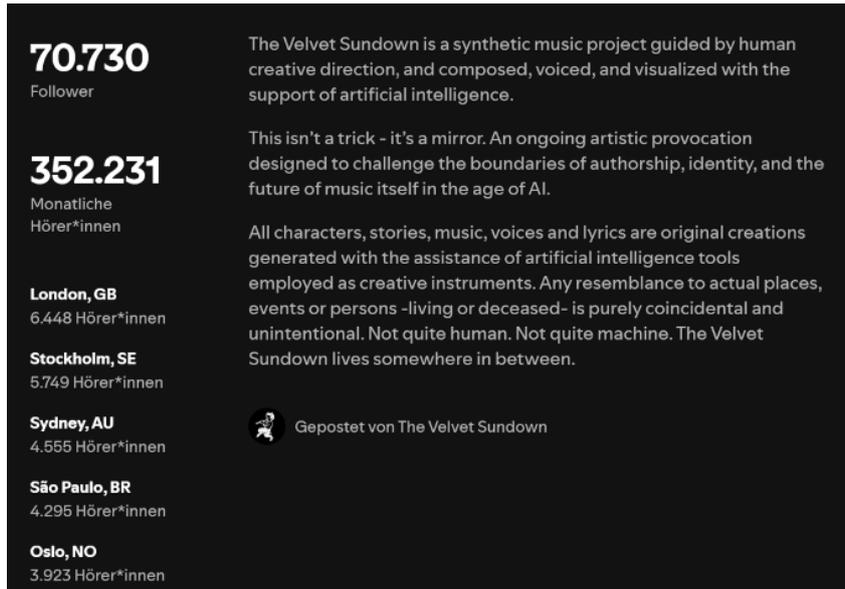


Figure 1: 'About the artist' The Velvet Sundown on Spotify

To understand consumers' preferences and willingness to pay for AI-generated music, we present three empirical studies. In Study 1, we rely on panel data (six waves, 2018-2021, about 2,000 participants per wave) and measure attitudes toward the use of AI for music generation in a very early stage of AI diffusion (Chat GPT was released November 30 2022). We find that a majority of the respondents are not averse to AI-generated music. In Study 2, we complement these observational insights with results from a pre-registered 2x2 experimental study (N=425) that allows us to better understand how the use of AI (labeled as AI-generated music or not) affects listeners' preferences over entire playlists and individual songs. We use electronic dance music and vary whether songs are with or without vocals to test whether AI preferences differ between vocal and instrumental music. We find that AI source disclosure does not result in inferior evaluations of songs or playlists. In Study 3, we conduct another pre-registered 2x2 experimental study (N=1,248), varying whether a song is actually human-made or AI-generated (song origin) and whether the listener receives this information or not (disclosure of AI) for pop and electronic dance music songs. By including human-made songs, we avoid any deceptive statements about the source of the music. In addition to stated preferences, we also elicit an incentivized measure of willingness-to-pay (WTP) for the songs. We find that AI-generated songs are perceived as being superior; however, if the music is disclosed as AI-generated, the willingness to pay decreases. This effect is mainly driven by pop listeners.

Our results extend prior research that has largely neglected customers' perception of AI-generated music. We find that AI-generated music is not perceived as inferior and process and outcome thereby taking full responsibility. See Chapter IV, Article 50(4) of the AI Act (European Union, 2024).

may therefore play a major role in consumers' future listening behavior of songs and playlists. This finding is contrary to previous findings describing a devaluation effect of AI-generated music (see e.g. [Tigre Moura and Maw, 2021](#); [Tubadji *et al.*, 2021](#)). While we rely on pop and electronic dance music, which represent a share of 38% of the total streams in 2024 in Germany ([Bundesverband Musikindustrie e.V., 2025](#)), others have focused on classical music, which only represents 1% of all streams in Germany in 2024. Furthermore, we overcome methodological limitations by [Tigre Moura and Maw \(2021\)](#), as we rely on an incentive aligned measurement of willingness to pay.

Our findings provide three insights for relevant stakeholders in cultural industries:

1. AI-generated music is well perceived by consumers and AI will support artists in creating, producing, and distributing music faster (and maybe even with higher quality).
2. However, the widespread availability and usability of AI tools (e.g., MusicLM or Suno), even for non-experts, will result in lower market entry barriers for non-artists that target the royalty pools of streaming services. While one may argue that this is a democratization of music generation, others may argue that it will result in job displacement and a devaluation of the skills of human musicians.
3. The risk of royalty pool dilution cannot be denied, as creating high-quality content at little to no cost is a potentially profitable strategy as consumer generally react to it positively. However, there is a risk for streaming platforms, as AI-generated music potentially leads to lower willingness to pay if songs are labeled as AI-generated, which will reduce the size of the royalty pool. These insights can be generalized to other industries that rely on global platforms that offer large digital assortments to customers using a subscription model. For example, in the publishing industry, platforms offering e-books are also confronted with a large number of books generated by AI.

The article proceeds as follows: In Section 2, we present the context of our studies by discussing previous empirical studies of how AI may influence music production and consumption. We then provide an overview of our three studies (Section 3) and conclude with a discussion of our studies' implications in Section 4.

2 Background

The adoption of AI technology has the potential to substitute for human effort in a number of tasks, thereby destroying or fundamentally transforming occupations. The implications for work and its meaningfulness have been explored in a number of articles.

Cordasco and Véliz (2025) argue that the widespread adoption of AI may reduce the opportunities of individuals to gain self-esteem through their work. First, the reliance on AI may directly reduce self-esteem if the AI consistently outperforms the human (Cordasco and Véliz, 2025), if it erodes a former qualitative work experience as is found for automation of tasks more broadly (Spencer, 2023), or if collaboration with AI induces doubts about over creative control and authorship (Xu *et al.*, 2025). Second, reliance on AI may indirectly threaten self-esteem and meaning from work as it reduces possibilities to earn ones living from it through its effect on remuneration models. By zooming in on the valuation of consumers for AI-generated music, our studies speak to this indirect effect, which plays a crucial role in our modern world where compensated work is a central source of meaning (Mejia, 2023).

According to previous psychological research, aesthetic appreciation and judgment of music (Brattico *et al.*, 2013) as well as visual arts (Chatterjee and Vartanian, 2014) are influenced by context. The information who created a piece of art or who has composed a piece of music is one natural aspect of the context in which art is appreciated, and it has been shown to affect judgments, for instance, of visual art (Darda and Chatterjee, 2023) and classical music (Fischinger *et al.*, 2020), where information on the (famous) creator positively influences experiences. Previous research further found that consumers are sensitive to information and beliefs about the cultural origins of music (Chilvers *et al.*, 2024).

Turning to the impact of AI on judgments, Shank *et al.* (2023) find that a piece of classical music was liked less if believed to be AI-generated, as compared to human-made, but they did not find a similar preference against AI for electronic music. In addition to the music's genre itself, the listener's personal taste for a genre also plays a role: Tubadji *et al.* (2021) argue that fans of pop and rock music in their sample responded more strongly to information about a piece of music being AI- versus human-generated than those who had a taste for classical music. In their study, participants listened to AI-generated as well as human-composed music and stated their evaluation twice, first without and then with information about the composer being AI or human. Tubadji *et al.* (2021) find that the disclosure of the source is more likely to decrease the evaluation of AI-generated music than of a human compositions, and is less likely to result in an increase in the evaluation of AI- than of human-generated music. According to the authors, their findings imply that consumers are willing to discriminate against AI-generated music. In contrast to the studies by Shank *et al.* (2023) and Tubadji *et al.* (2021), which focused on specific pieces of music, Tigre Moura and Maw (2021) studied consumer attitudes with respect to AI-generated music more generally. In a first study, the surveyed respondents declared that they liked AI-generated music less and stated low likelihoods of purchasing it; results were similar for music listeners and music professionals. In a second study,

Tigre Moura and Maw (2021) ran a laboratory experiment using audio samples of AI-generated music, where they manipulated whether participants were told that the music was generated by an AI or by a human. In this experiment, however, they did not find a bias against the use of AI in the subjects' evaluations.

Similar to the negative effect of disclosed AI-use observed in music appreciation, disclosing that content is AI-generated has been found to negatively affect evaluations across a variety of domains. In contexts such as health communication (Karinshak *et al.*, 2023; Lim and Schmäzle, 2024), news consumption (Longoni *et al.*, 2022), and creative writing (Abel and Johnson, 2025), disclosure has been shown to reduce perceived credibility, accuracy, and subjective assessments. Similarly, studies on human–AI interaction highlight that consumers react negatively when learning that a conversational agent is AI-powered (Luo *et al.*, 2019), and evidence from advertising suggests that revealing AI-origin can diminish persuasive effectiveness, thereby lowering donation intentions (Arango *et al.*, 2023). However, the use of AI is not always judged negatively. In an experiment with more complex news articles that involved evaluative statements, Henestrosa *et al.* (2023) did not find a negative effect on perceived credibility or trustworthiness when the author is allegedly an AI versus a human. Similarly, studies on consumer behavior suggest that willingness to pay does not differ between human- and AI-generated content (Abel and Johnson, 2025; Lane *et al.*, 2025), and AI-authored messages can be just as effective as those written by humans (Gallegos *et al.*, 2025; Huang and Wang, 2023).

A possible explanation for the sometimes observed bias against AI is that people perceive work by AI as less authentic than work created by human creators (Jago, 2019). At the same time, the instability in results is consistent with the finding that the influence of AI-use in the generation of artwork depends on the exact way in which it is communicated: In experiments by Epstein *et al.* (2020) respondents attribute less responsibility and less credit to the AI when it is described as a tool used by a human creator than when it is anthropomorphized and characterized as exhibiting autonomy and agency in the creation process of the artwork. Their findings indicate that the effect of AI-use on the evaluation of the resulting art products will depend on the language and framing chosen to describe the use of AI in the generation process.

As the technology for AI-generated music has advanced and AI generated music is streamed more often, even reaching top positions in music charts, the question of how consumers react to AI generated music becomes increasingly valid for artists, labels, and platforms. We present new insights from three studies with respect to the preferences of consumers regarding AI-generated music and how their willingness-to-pay is influenced when the source of creation is revealed using incentive aligned methods. These studies also allow to assess potential consequences from initiatives demanding that AI-generated content be labeled as such.

3 Empirical analysis

The analysis of previous work with respect to AI generated music revealed inconclusive insights. While some authors found no effect (Tigre Moura and Maw, 2021, Study 2), most research found a tendency towards more negative perceptions of AI-generated music. However, these studies neglected monetary outcomes of these perceptions, or were not methodologically sound with respect to measuring the WTP.

Therefore, we advance the field through three complementary studies. Each study addressed a different aspect of evaluation and behavior, ranging from general attitudes to concrete song evaluations and willingness-to-pay. An overview of the studies is provided in Table 1, while the subsequent sections describe each study in greater detail.

Table 1: Overview of all conducted studies

	Study 1	Study 2	Study 3
Question	How is the acceptance of AI-generated music in general and how did it develop over time?	Is the preference for music in a playlist environment influenced by whether the music is generated by a human musician or through AI?	Is the preference for a single song influenced by whether the music is generated by a human musician or through AI, and how does this translate into monetary evaluation? Does it differ between different subsamples (genre, lifestyle)?
Method	Longitudinal panel survey with 6 waves over three years	Experiment with a 2x2 between subject design: Info vs. No Info Instrumental vs. vocal	Experiment with a 2x2 between subject design: Human vs. AI Info about origin vs. No info
Outcomes	Agreement on a 7-point Likert scale with the statement: <i>“I reject musical compositions that are not created by humans”</i>	Evaluation of each single song and the overall playlist	Song evaluation and incentivized WTP for the song
Results	(1) No clear rejection of non human compositions, (2) no trend over time	No difference in evaluation of the song or playlist	(1) Participants evaluated AI-generated music more positively, (2) but showed a lower WTP. (3) The first effect was driven by pop listeners, (4) while lifestyle listeners showed no significant reaction.

3.1 Study 1

In our first study, we examined data gathered over a three-year period (2018-2021) from a longitudinal panel survey conducted in Germany. The data was made available to us by Clement and Kandziora (2021). The panel study was designed to track changes in music

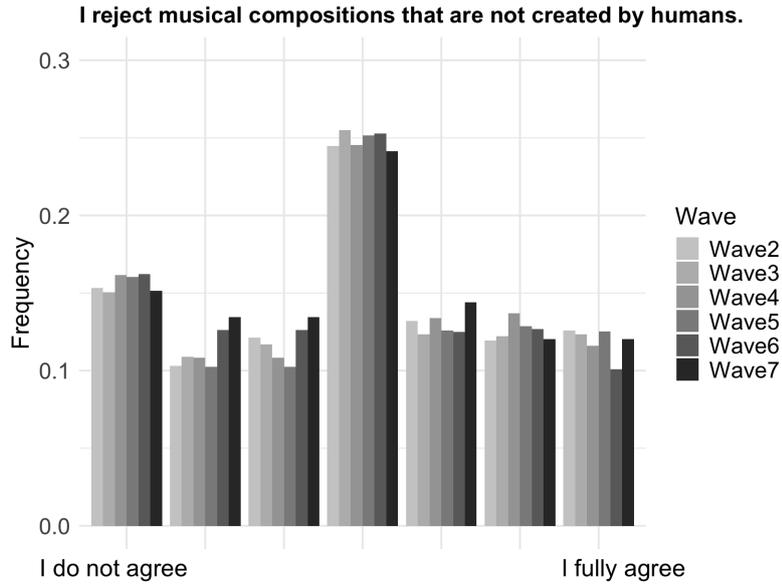


Figure 2: Development of rejection of non-human musical compositions

Notes: The question was only included from Wave 2 onwards. Average number of participants N=2040.

preferences, consumption behavior, and related topics over time. Participants responded to a wide range of questions related to music streaming, live music events, and music discovery, among other topics. The study started with 5,140 participants in wave 1. The average number of participants per wave across the duration of the study was 2,040.

In the second wave of the study, an additional item was introduced to assess attitudes towards “non-human compositions,” which was employed to investigate the extent to which the general public is willing to accept music generated by artificial intelligence. Participants were asked to indicate their level of agreement with the statement, “I reject musical compositions that are not created by humans,” using a seven-point Likert scale. This variable was also asked in all subsequent waves.

On average, there is little indication that participants have an aversion against AI-composed music. Figure 2 shows that the modal answer was indifference, and about as many participants agreed and did not agree with the statement. Moreover, this answer pattern remained relatively stable throughout the three years of data collection. However, the aggregate data hides relevant heterogeneity in attitudes by the preferred music genre of the respondents: The rejection of musical compositions not created by humans varies significantly by genre. Listeners of electronic dance music were, on average, more likely to accept AI-composed music, while classical music listeners were more likely to reject it; pop listeners exhibited no clear preference (see Figure 3). These results provide a valuable first insight into how music audiences view the evolving role of AI in creative processes, highlighting both stability and diversity in responses over time.

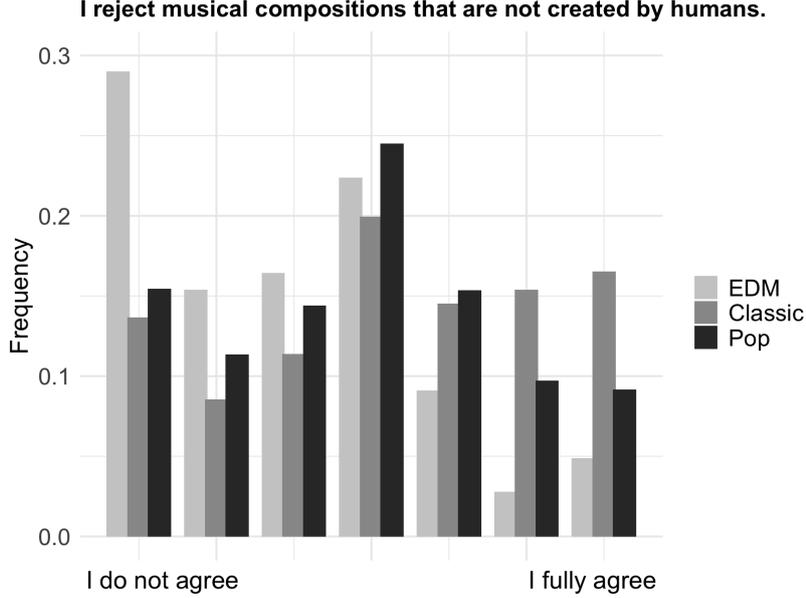


Figure 3: Heterogeneity in the rejection of non-human musical compositions.

Notes: Data from Wave 7. Genres assigned based on respondents' selection in the question: "Which of these genres best describes your taste in music?" (Multiple selections allowed.) Participant counts: Pop (N = 1,048), Classical (N = 351), electronic dance music (N = 286).

These results suggest that, in contrast to previous results on AI bias in the literature, the average music listener may not be averse to the use of AI in music generation. However, respondents only reported their attitudes while not being confronted with an actual listening experience. We therefore designed two complementary experimental studies to study the causal effect of AI use on preferences and willingness-to-pay for music. The goal of these two studies is to systematically investigate a potential bias against AI music in a controlled environment. For the first experiment (study 2), we focus on electronic dance music (electronic dance music) and a playlist environment, which mimics the way how participants listen to music in their preferred streaming service. For the second experiment (study 3), we focus on individual songs and complement treatments with electronic dance music (electronic dance music) with treatments using pop music to address the heterogeneity in attitudes toward AI use that is suggested by the panel data.

3.2 Study 2

Our second study was a pre-registered online survey. After completing an initial screening, participants provided information on their sociodemographic characteristics, listening habits, and general attitudes toward music. Participants were then randomly assigned to one of four experimental conditions described below.

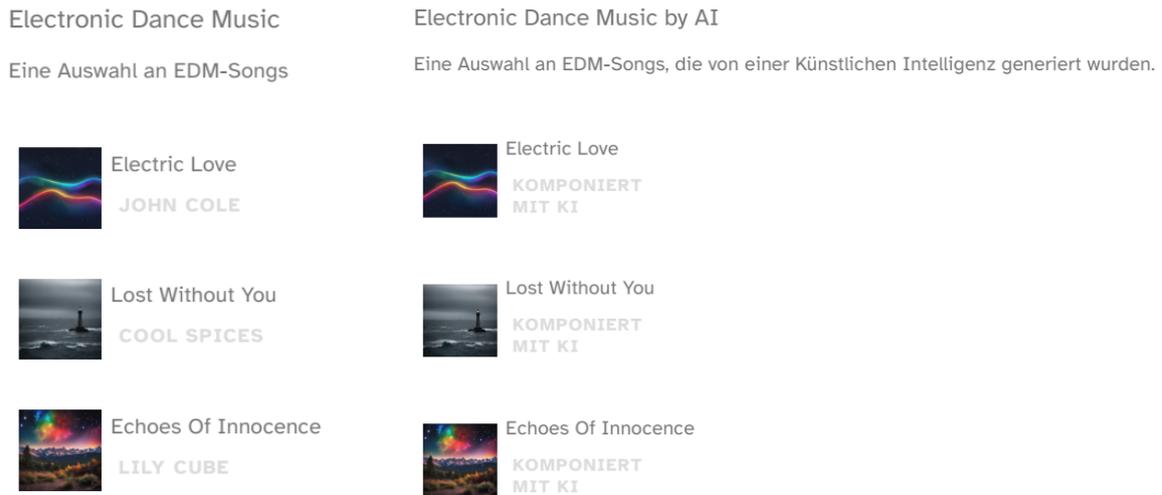


Figure 4: Display of playlists

Notes: Display are for treatments with instrumental music for NOINFO (left) and for INFO with information about the use of AI (right). The subtitle translates as “A selection of electronic dance music songs” (left) and “A selection of electronic dance music songs that were generated by an artificial intelligence” (right). Instead of an artist name, songs in INFO were labeled as “composed with AI”.

Design In all conditions, participants were shown a playlist with three tracks, which they had to listen to one after the other. All tracks used in the playlists were electronic dance music generated with generative artificial intelligence. The presentation of the playlist aimed to replicate the aesthetic of a typical Spotify playlist. For each song, participants had to assess their listening experience right after listening to it. They indicated how much they liked the respective track (7-point Likert scale, *Like Song*) and the likelihood of listening to that track again (7-point Likert scale, *Relisten Song*). As an attention check, they had to answer a question about a possible vocal part of the track. Upon completing the third song, they also provided an overall evaluation of the playlist (7-point Likert scale, *Like List*). Following these evaluations, the survey additionally elicited participants’ attitudes toward the use of AI in the music industry and their broader perspectives on emerging technologies.

We implemented a 2x2 between-subjects design and varied a) whether playlists were labeled as AI-generated (INFO) or not (NOINFO) and b) whether the playlist tracks contained vocals or were purely instrumental. In the NOINFO treatments, where the playlist and its tracks were not labeled as AI-generated, participants saw a fictitious artist name and song title next to a cover picture. In the INFO treatments, they saw the same cover and song title, but instead of an artist name the label ‘Composed with AI’ was displayed alongside the song. Further, the playlist was described as a selection of songs in the NOINFO treatments, and as a selection of songs that were generated by AI in the INFO treatments. Figure 4 provides screenshots of the playlist screen for the two treatments for the treatment arm with instrumental music.

Procedures The study was pre-registered before data collection started under AsPredicted #169399.³ The survey was programmed using SoSciSurvey. Participants were recruited through Bilendi in April 2024. At the recruitment stage, we screened participants according to their preferences over music genres and kept only those who indicated electronic dance music as one of the genres they enjoy listening to. We used quotas to target a balanced distribution over five age groups and gender. Participants were compensated for the time by the survey provider.

Sample The survey was completed by 713 participants in total, of whom 425 remained after applying a set of pre-specified exclusion criteria. Specifically, we excluded individuals who failed an attention check, who completed the survey in less than 80% of the median completion time, or who did not answer all questions. In addition, we also excluded those who were able to bypass the minimum required 30 seconds on pages with the songs playing.

In the final sample of 425 participants used for analysis 52.71% identified as female, 46.82% as male, and 0.5% as diverse and participants are distributed roughly equally over the five targeted age groups (18-24 year old: 19.76%, 25-34 years old: 17.89%, 35-44 years old: 19.29%, 45-54 years old: 20.94%, above 54: 22.12%). On average, participants spent 10 minutes on the survey and the median completion time was 9 minutes and 54 seconds.

Descriptives Participants reported listening to electronic dance music on average 3–4 times per week and listening to music in general for more than one hour per day. Nearly 82% reported using a music streaming service, primarily a premium version.

Attitudes toward the use of AI as a tool to support music creation were relatively positive (mean = 4.23 on a 7-point Likert scale, where 1 = “I do not agree at all” and 7 = “I fully agree” to the statement “Human artists should use AI as support (e.g., to find missing lyrics or to be more creative)”) but agreement decreased when it came to using AI to entirely generate songs or to “bring back” deceased artists. Participants also indicated a general openness toward new technologies (mean = 4.79 on a 7-point Likert scale).

Turning to the attitudes to the songs used in the experiment, we observe that participants on average liked the songs they heard, with an average rating of 4.40 for individual songs and 4.36 for the playlist (on a 7-point Likert scale, where 1 = “Very bad” and 7 = “Very good”). They stated on average more often to be at least somewhat likely to relisten to the songs than to be somewhat or very unlikely to do so (average score 3.98, where 1 = “Very unlikely” and 7 = “Very likely”).

³Available at <https://aspredicted.org/j44p-h9p4.pdf>.

Table 2: Treatment comparison of average music evaluation in NOINFO and INFO split up by vocal and instrumental conditions.

Condition	Measure	Info	NoInfo	t-value (p-value)
Vocal	Song Rating	4.16	4.48	-1.80 (.073)
	Listen Again	3.69	4.07	-1.88 (.062)
	Playlist Rating	4.06	4.43	-1.83 (.07)
Instrumental	Song Rating	4.46	4.43	0.18 (.857)
	Listen Again	3.92	4.14	-0.92 (.361)
	Playlist Rating	4.32	4.54	-0.92 (.361)

Notes: Song rating (Listen Again) is the individual-level average over an individual’s three 7-point Likert scale ratings (relistening scores) for the three songs. Playlist is an individual’s rating of the entire playlist on a 7-point Likert scale. The table reports averages by condition and treatment.

Results The following analysis is based on two hypotheses that we pre-registered before collecting the data. Our first hypothesis is that participants rate the listening experience of AI-generated music worse when informed about the AI-origin. The second hypothesis is that this bias is stronger for music containing vocals than for instrumental music. We investigate these hypotheses using all three measures of listening experience: Participants’ stated probability of relistening to individual songs, their liking ratings for each song, and their overall evaluation of the playlist.

To test the first hypothesis, we pool data from the groups with instrumental and vocal music and compare evaluations between NOINFO and INFO treatments. We find no significant difference in the stated music ratings at either the individual song level ($t = -1.057$, $p = 0.291$) or at the playlist level ($t = -1.784$, $p = 0.0752$). The stated relistening probability does not differ significantly with the absence or reception of information about AI use either ($t = -1.876$, $p = 0.0613$).

We then tested whether the AI composer bias was more pronounced for vocal music compared to instrumental music to address the second hypothesis. While we observe a slightly larger effect of the information about AI use on ratings for vocal pieces than for instrumental pieces, the treatment difference does not reach statistical significance in either the instrumental or vocal music condition. See Table 2 for details.

We further explore heterogeneity with respect to the amount of time participants spend listening to electronic dance music per week. The results, shown in Table 3 suggest that heavier listeners of electronic dance music respond more negatively to the information about AI origin. We find a significantly negative interaction effect between information about AI origin and time spent listening to electronic dance music for the average song rating. The interaction effect in the regressions of relistening probability and the overall playlist evaluation do not gain significance at conventional levels but go in the same direction with p-values below 0.1. Thus, while the main effect of knowledge about AI

Table 3: The moderating effect of time spent listening to electronic dance music per week on song- and playlist evaluation.

	<i>Dependent variable:</i>		
	Song Rating (1)	Listen Again (2)	Playlist Rating (3)
Info	0.554 (0.358)	0.437 (0.437)	0.469 (0.441)
Time	0.207*** (0.068)	0.243*** (0.083)	0.254*** (0.084)
Info*Time	-0.215** (0.105)	-0.227* (0.128)	-0.234* (0.129)
Constant	3.792*** (0.233)	3.325*** (0.284)	3.661*** (0.286)
Observations	425	425	425
Adjusted R ²	0.017	0.021	0.022
F Statistic	3.491**	4.071***	4.184***

Notes: Results using OLS. Info is a dummy taking the value 1 for participants who received information about the AI origin of the song, 0 otherwise. Time measures the hours a participant stated listening to electronic dance music per week. Song rating (Listen Again) is the individual-level average over an individual’s three 7-point Likert scale ratings (relistening scores) for the three songs. Playlist is an individual’s rating of the entire playlist on a 7-point Likert scale. *p<0.1; **p<0.05; ***p<0.01

origin is not significant, the results reveal a very intuitive heterogeneity in reactions: Frequent listeners of electronic dance music react more negatively to the information about AI-use than those listening to electronic dance music less often.

3.3 Study 3

The third study was another pre-registered online survey. It complements the previous two studies by zooming in on preferences about AI use at the individual song level. In contrast to study 2, we actually include both AI-generated and human-made songs to provide clean evidence for whether songs are generally liked less if they are generated by AI or whether the negative effect relates to being informed about it. In addition to unincentivized survey measures, this study also uses an incentive-aligned measure of willingness-to-pay to assess the possible monetary consequences of the use of AI in music generation on consumer surplus.

Since openness to innovation has been shown to correlate with the taste for certain genres, we expect the effect of AI information to potentially differ across genres. Therefore, we include both electronic dance music and pop music in our study. Specifically, [Rentfrow and Gosling \(2003\)](#) found that individuals with a preference for music classified

as Energetic and Rhythmic tend to be more liberal and less conservative, more agreeable and more extroverted, whereas those preferring music classified into Upbeat and Conventional tend to be also more extroverted and agreeable, but also more conscientious, less open to new experiences, less liberal, and more conservative. With electronic dance music falling into the first and pop into the second category, it would not be surprising to find that AI aversion is stronger among pop listeners than among those listening to electronic dance music.

Design An initial screening was used to identify regular listeners of electronic dance music or Pop Music to recruit participants for the two survey branches studying electronic dance music and Pop Music. Participants were then split into two groups, listeners of electronic dance music and Pop listeners, based on their stated listening preferences and channeled to two survey versions that used songs matching these genres (electronic dance music and Pop).⁴ In both groups, we implemented four experimental conditions described in detail below. All participants were asked about their music listening behavior, their music preferences, and their average spending on music, merchandise, and tickets, and then had to listen to one song that varied with the experimental condition. Each song lasted about 3 minutes and participants could proceed to the next page of the survey at the earliest after 60 seconds.

In conditions 1 and 3, participants listened to a song from an unknown human composer; in conditions 2 and 4, they listened to a song generated through an appropriate AI application. While participants in conditions 1 and 2 received no specific information about the source of the song, participants in condition 3 were informed of the AI origin of their song, and participants in condition 4 were informed that the song was composed by a human musician after their initial judgment upon listening to the song.

Immediately after listening to the song, all participants were asked to state how much they liked the song on a 7-point Likert scale (*Like*) and the likelihood that they would relisten to the song if given the possibility to do so from the interval $[0, 100]$ (*Again*). The relistening probability *Again* was elicited right before subjects in conditions 3 and 4 were informed about the AI or human origin of the song. On the screen with this information, we asked whether the participant would like to adjust their relistening probability (*Again_Info*).⁵ All participants were asked to state their willingness-to-pay for a digital copy of the song (WTP_{Song}). We elicited this WTP with a random price

⁴At the start of the survey, participants were presented with a list of 16 music genres and asked to select the one(s) that best described their musical preferences. Those who selected only Pop or only electronic dance music were assigned to the corresponding questionnaire. Participants who selected both were assigned to the electronic dance music questionnaire, due to the smaller proportion of listeners of electronic dance music in the sample. Those who selected neither of the two genres were screened out.

⁵For part of the sample, that was collected in the second wave (see procedures), we additionally asked whether they would like to adjust their song evaluation on the Likert scale (*Like_Info*).

mechanism (Becker *et al.*, 1964) which assigned equal probability to all prices in Eurocents between 0.00 and 2.00 Euros. Participants received an extra endowment of 2.00 Euros to spend on the song and were asked to state which amount between 0.00 and 2.00 euros they would be willing to pay to download a digital copy of the song they had listened to.⁶ Only if a participant’s stated WTP exceeded the randomly drawn price, they would receive a download link for the song and the price would be subtracted from their endowment. The remainder or the full endowment, in case the stated WTP fell short of the randomly drawn price, were added to the final remuneration of the participants upon completion of the survey. Additionally, we elicited hypothetical willingness-to-pay for a concert ticket of the artist behind the song, for a standard monthly streaming subscription and for a monthly streaming subscription featuring only AI-generated music.

The design implies that the variable *Like* can only be used for between-subject comparisons that address the question whether AI-generated songs are liked more or less than human-made music without knowing the true origin of a song. The variables *Again* and *Again_Info* together allow for both a between-subject comparison of relistening probabilities prior to receiving the information, a within-subject comparison of relistening probabilities prior to and after receiving the information, and a between-subject comparison of the relistening probabilities after receiving the information. The WTP for the song was elicited after the information intervention making, it suitable only for between-subject comparisons.

Pretest We ran a pre-test to investigate whether participants could recognize the songs used in our study as being created by a human or with the help of an AI. In line with previous results on piano performances (Schubert *et al.*, 2017) and visual arts (Gangadharbatla, 2022), this was not the case.⁷ Excluding answers in which respondents selected “I don’t know,” we analyzed the data using a mixed-effects logistic regression with random intercepts for participants and songs, testing the intercept against chance (50%). On average, participants were correct on 58.9% of answers (intercept logit = 0.360), a numerically above-chance rate, but the difference did not reach statistical significance ($z = 1.633$, $p = 0.103$), indicating no reliable ability to distinguish AI-composed from human-composed songs.

⁶The AI-generated music was not available on any platform, meaning participants could not access these songs elsewhere. In contrast, the human-composed songs were technically accessible via streaming platforms or purchase, but we deliberately selected relatively unknown Irish artists (with only 17 and 1,700 monthly listeners on Spotify). The songs were presented without any information about the artists or titles. While it cannot be entirely ruled out that participants may have encountered the songs through other means, the likelihood of this is negligible.

⁷In contrast to our study, where the songs were not only performed but also composed by a computer, the study by Schubert *et al.* (2017) is only concerned with the question of performance by an AI.

Table 4: Distribution of participants over four treatments and two genre conditions.

	electronic dance music	Pop	Total
Human INFO	192	214	406
Human NOINFO	101	106	207
AI INFO	202	220	422
AI NOINFO	104	109	213
Total	599	649	1248

Procedures For this study, we collected data in two waves. Conditions 1, 2, and 4 were included in the first wave, whereas the second wave only included conditions 3 and 4. Participants were recruited through Bilendi in April and November of 2024. The study was pre-registered under AsPredicted #171561 (wave 1) and #198622 (wave 2).⁸ At the recruitment stage, prospective participants were screened according to their preferences over music genres. Only those indicating electronic dance music or pop music as a preferred genre were forwarded to the study, allocating them to the treatment arms with electronic dance music and Pop Music, as described above. Quotas were used to target a balanced distribution over five pre-specified age groups (18-24 years old, 25-34 years old, 35-44 years old, 45-54 years old, above 54 years old) and gender. Participants were compensated for the time by the survey provider. All information in the study was true. The human-made songs were actually composed by unknown human artists. The AI-generated songs were generated by an AI application being prompted by us.⁹

Sample From 1257 participants who completed the survey, we excluded nine participants who failed an attention check, who completed the survey unreasonably quickly, and those whose total listening time of music per week exceeded the time available in a week. These exclusions conform with the preregistered exclusion criteria. The final sample contains 1248 participants. The distribution over treatments, split by genre, is shown in Table 4.

The sample is approximately balanced between female (50.8%) and male (48.9%) participants, with a small fraction identifying as diverse (0.3%). Chi-square tests reveal no significant differences in the gender distribution by questionnaire type electronic dance music/pop ($\chi^2 = 3.85$, $p = 0.146$) or over the eight combinations of treatment and genre ($\chi^2 = 9.66$, $p = 0.787$). The realized age distribution is not perfectly balanced, but we have an overrepresentation of age groups 45-54 years and 54 years and older (26.6% and 26.7% respectively; see Table 10). A chi-square test indicates no significant

⁸Available at <https://aspredicted.org/nwzc-bjf8.pdf> and <https://aspredicted.org/4tdp-47r2.pdf>.

⁹More information, including the prompts used, are available on request.

association between age group and allocation of the electronic dance music/Pop version ($\chi^2=7.26$, $p = 0.123$), but a significant association between age group and treatment condition ($\chi^2 = 41.48$, $p = 0.049$). We will, therefore, control for age groups in later regression analyses. The overall median income was in the category of 3000-5000€, and the median educational level was a high school diploma (Abitur); neither income nor education correlate significantly with treatment or genre.

On average, participants reported music to be quite important to them with an average score of 6.15 on a scale from 1 (very much unimportant) to 7 (very important) and we find that music is significantly more important in our electronic dance music sample (mean = 6.31) than in the Pop sample (mean = 5.99, $\chi^2 = 40.12$, $p < 0.001$). This fits with the observation that participants in the Pop sample reported listening to music significantly fewer hours per week than those in the electronic dance music sample (mean Pop = 18.55, mean electronic dance music = 22.81, $t = -3.45$, $p < 0.001$) and that digital music purchases were significantly higher among listeners of electronic dance music compared to Pop listeners ($\chi^2 = 11.80$, $p = 0.019$). Participants in the Pop sample also stated to listen more passively to music than those in the electronic dance music sample (mean Pop = 41.93, mean electronic dance music = 34.88, $p = 0.093$).¹⁰ These differences suggest that a differentiated analysis by survey version may be interesting.

Regarding their attitudes toward the use of AI in music generation, participants generally think that it is relatively easy to create a piece of music using AI (mean = 2.18), and this perception is more pronounced in the electronic dance music sample than in the Pop sample (mean electronic dance music = 2.05, mean Pop = 2.29, $p < 0.001$). Moreover, participants were moderately supportive of AI as an aid in music creation (mean = 3.29), and again perceptions differed significantly by genre with greater support expressed in the electronic dance music sample (mean electronic dance music = 3.50, mean Pop = 3.09, $p = 0.002$).

Descriptives Overall participants liked the songs they heard, rating them on average with 4.46 on a scale from 1 (not at all) to 7 (excellent). In the absence of information about the song’s composer, the AI-generated songs received a significantly higher rating on average than the songs created by humans (mean AI: 4.68, mean human: 4.22, $p < 0.001$) and participants stated a significantly higher relistening probability (*Again*) for the AI-generated songs than for the human songs (mean AI: 48.55, mean human: 39.26, $p < 0.001$). This difference remains significant when considering the informed relistening probability *Again_Info* for participants in conditions 3 and 4.

¹⁰The underlying question asks participants to position themselves on the range from active (0) to passive (100) with respect to their music listening.

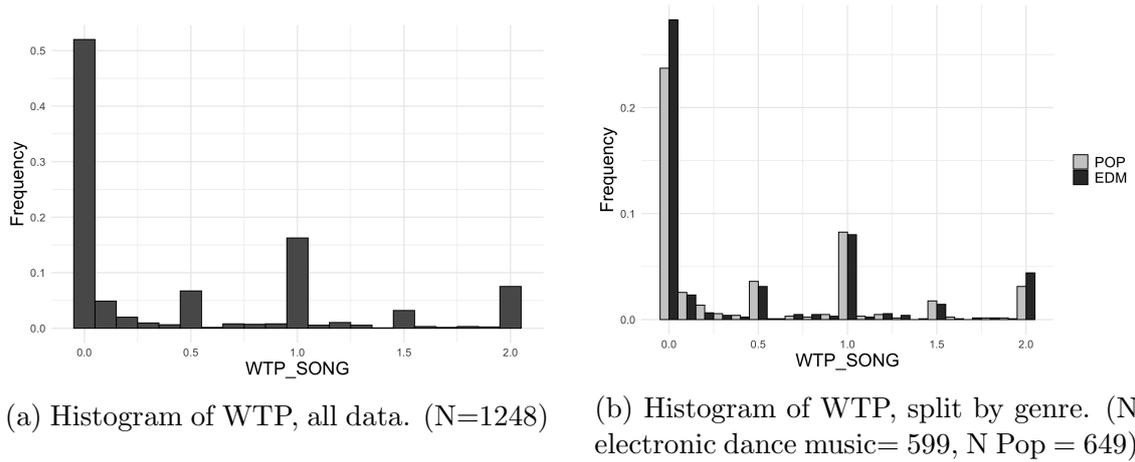


Figure 5: Histograms of stated WTP for the songs.

On average, participants were willing to pay 0.48 € for the song they had listened to. The distribution of WTP, however, is highly skewed as illustrated in Figure 5: Nearly half of all participants stated a WTP of zero. This pattern is similar in the electronic dance music and Pop samples and consistent with the typical music consumer’s preference for streaming services with a flat fee structure. The stated WTP is slightly higher on average for the human songs than for the AI songs, though the difference is not statistically significant ($t = 0.283$, $p = 0.777$).

Results To examine the presence of a potential bias against AI-generated music, we had pre-registered four hypotheses that are the basis for the following analyses. Our main focus lies on the stated relistening probability as a proxy for the participants’ liking of the song as an outcome variable. As this variable is elicited twice for participants in the INFO treatments, this variable is suitable for both between- and within-subject analyses of the effect of AI-use and knowledge thereof on song liking. We complement the analysis with between-subject comparisons of song liking using the ordinal variable *Like* and the elicited WTP.

We begin with the first hypothesis, that participants like AI-generated music less than human-composed music. To obtain a comprehensive perspective on the validity of this hypothesis, we test a between-subject and a within-subject version of it. First, we compare the informed relistening probabilities (*Again_info*) of participants in the HUMAN INFO treatment to those of participants in the AI INFO treatment. Participants who were informed that the music was AI-generated stated on average significantly higher relistening probabilities than those who were informed that they had listened to a human-composed song (means of 46.69 versus 38.56, $t = 3.42$, $p < 0.001$ in a two-sample t-test, see also Figure 6, left panel, and columns 1 and 2 in Table 5).¹¹ Next, we compare

¹¹During the second wave of the study, we also collected the general song evaluation twice, once before (*Like*) and a second time after (*Like_Info*) providing information about the song origin. Since these

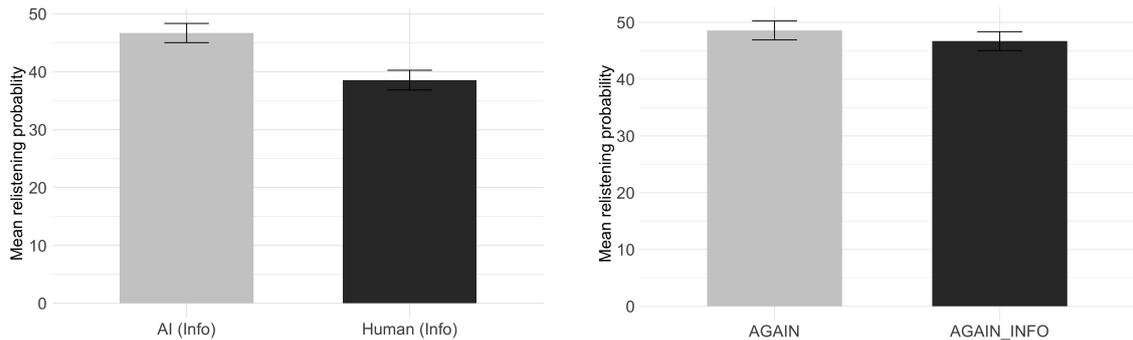
Table 5: The effect of AI use on informed relistening probabilities and WTP

	<i>Dependent variable:</i>			
	Again Info		WTP Song	
	(1)	(2)	(3)	(4)
AI	8.133*** (2.378)	7.899*** (2.378)	-0.049 (0.043)	-0.048 (0.043)
Constant	38.557*** (1.698)	33.452*** (3.416)	0.460*** (0.031)	0.433*** (0.062)
Age groups	No	Yes	No	Yes
Observations	828	828	828	828
Adjusted R ²	0.013	0.019	0.0003	0.002
F Statistic	11.699***	4.138***	1.283	1.368

Notes: OLS with subset of participants who got information about song origin. AI as a dummy for participants who listened to a song that was AI-generated. Regressions for columns (2) and (4) include age group dummies. *p<0.1; **p<0.05; ***p<0.01

how relistening probabilities changed upon becoming informed about the origin of the song by comparing *Like* to *Like.info* at the individual level. A paired t-test shows that participants who had listened to an AI-generated song significantly decreased their stated relistening probability once they learned that it was AI-generated (means of 48.57 before versus 46.69 after, $t = 3.24$, $p = 0.0013$, see also Figure 6, right panel). We do not find a significant change in the relistening probability for those participants who were informed about the human origin of the song they had listened to (means of 38.83 before versus 38.56 after, $t = 0.511$, $p = 0.6096$). The general song evaluation confirms this picture: In the subsample from wave two for which song liking was elicited twice, we find a significantly negative effect of the information that the song was AI-generated (means of 4.78 before versus 4.62 after, $p < 0.001$) but no significant effect of the information that the song was human-made (means of 4.2 before versus 4.17 after, $p = 0.201$). In summary, we do not find evidence that AI-generated music is generally liked less even if participants are informed about the use of AI (between-subject comparison), but we find a significantly negative effect of receiving the information about AI-use in a within-subject analysis. These findings partially confirm an aversion against the use of AI, which is blurred in between-subject comparisons due to the participants generally high appreciation of the AI-generated music when uninformed.

Put together, we observe two opposing effects that play out differently in the between- and within-subject comparisons: On the one hand, music that is accessible and familiar is generally liked more, and since a generative AI is trained on existing music, it is likely to produce exactly that type of music. This effect dominates the between-subject evaluations are also significantly higher for AI-generated songs (means of 4.62 versus 4.17, $t = 3.51$, $p < 0.001$), it appears unlikely that the effect on the likelihood of listening again is merely driven by curiosity.



(a) Comparison of informed relistening probabilities between AI and human songs. (N=828)

(b) Comparison of relistening probabilities for AI songs before and after information. (N=422)

Figure 6: Effect of information about AI/human origin on stated relistening probabilities.

comparison. The within-subject comparison, on the other hand, controls for the baseline liking of the song that reflects the general likeability of the AI-generated music and isolates the negative effect of being informed about the use of AI versus human skill. We interpret the result to imply that the use of AI can generally influence the attractiveness of music to potential listeners but their experienced utility from the music is biased upwards if they are uninformed about the use of AI, as we find a significantly negative effect of information on stated relistening probabilities.

In addition to the previously stated attitudes, we also examined participants' willingness-to-pay (WTP) for the song as an alternative and incentive-aligned measure of song evaluation. As can be seen in columns 3 and 4 in Table 5, we find no significant difference in WTP for AI-generated as compared to human-composed music for the subset of informed participants. However, when comparing those participants who were uninformed that the music was AI-generated (treatment AI NOINFO) with those who were informed (treatment AI INFO), the informed participants stated significantly lower WTP for the AI-generated songs (mean informed: 0.41, mean uninformed: 0.59, $t = 3.248$, $p = 0.0013$). When comparing the WTP of participants in HUMAN NOINFO and HUMAN INFO, we do not find any information effect on WTP for human-made songs (mean informed: 0.46, mean uninformed: 0.53, $t = 1.1613$, $p = 0.2462$). These findings imply that information about the AI-origin of the song does not only shift reported relistening intentions and stated song liking, but these attitudes also translate into a systematic difference in participants' monetary valuation of the music, suggesting that AI use and (non-)disclosure of it may have monetary consequences for musicians and streaming services.

Since electronic dance music is mainly produced on computers and because the attitudes of a typical listener of electronic dance music may systematically differ from those of a pop listener according to results by [Rentfrow and Gosling \(2003\)](#), we next test our

Table 6: The effect of AI-use and genre differences on informed relistening probabilities and WTP

	<i>Dependent variable:</i>					
	Again Info		WTP Song		Δ Again	
	(1)	(2)	(3)	(4)	(5)	(6)
AI	3.347 (3.443)	2.974 (3.435)	-0.099 (0.062)	-0.104* (0.062)		
Pop	-6.325* (3.396)	-6.249* (3.389)	-0.021 (0.061)	-0.023 (0.061)	-1.439 (1.163)	-1.370 (1.173)
AI*Pop	9.110* (4.755)	9.419** (4.753)	0.096 (0.086)	0.107 (0.086)		
Constant	41.891*** (2.465)	36.887*** (3.870)	0.471*** (0.045)	0.447*** (0.070)	-1.134 (0.840)	0.880 (1.764)
Age groups	No	Yes	No	Yes	No	Yes
Observations	828	828	828	828	422	422
Adjusted R ²	0.015	0.021	-0.00003	0.002	0.001	-0.003
F Statistic	5.300***	3.579***	0.991	1.277	1.531	0.720

Notes: OLS estimates based on the subset of participants who received information about the song's origin. In columns 1 to 4, we include observations from treatments HUMAN INFO and AI INFO, in columns 5 and 6, we restrict attention to observations from AI INFO. AI is a dummy variable indicating participants who listened to AI-generated songs. Pop is a dummy variable indicating that the song's genre was pop. Δ Again is the relistening probabilities stated after minus the one state before information about song origin was given. Regressions for columns (2), (4), and (6) include age group dummies. *p<0.1; **p<0.05; ***p<0.01.

second hypothesis that the bias against AI as a composer is stronger for pop than for electronic dance music. Therefore, we analyze the effect of AI information separately for the two genres and investigate whether the interaction effect differs between samples of pop and electronic dance music.

We restrict attention to participants in the INFO treatments with AI and human songs and regress the stated relistening probability after learning about the song's origin (*Again Info*) on a dummy *AI* that takes the value 1 if the participant listened to an AI-generated song. The results are shown in columns 1 and 2 of Table 6: While the average relistening probability was, on average, lower for the human pop song than the human-made electronic dance music, the AI-generated pop music received on average higher relistening probabilities than its human-made counterpart, but we do not observe a meaningful difference between the human-made and AI-generated pieces of electronic dance music. As before, the effects are weaker when we consider the WTP in columns 3 and 4 of Table 6: If anything, we observe that WTP is on average lower for AI-generated songs than for human-made songs, but we find no indication that WTP are affected differently for pop or electronic dance music. Instead, we note that age helps to explain

WTP but AI versus human origin or genre do not explain a meaningful part of the variance in WTP.

We complement these insights from treatment comparisons with results from a within-subject analysis, where we only consider participants in the AI INFO treatments and investigate whether the individual-level reaction differs between the samples who listened to pop or electronic dance music. As shown in columns 5 and 6 of Table 6, the effect of disclosing AI-origin on the change in an individual’s stated relistening probability does not differ between the two groups with pop or electronic dance music. We also note that the model fit is extremely poor in these regressions.

Following the idea that the judgment of AI use for music generation may correlate with the importance that music plays in the life of listeners, our third hypothesis is that “lifestyle listeners” are more responsive to the song being AI-generated. As we are not aware of an established definition of what defines a lifestyle listener, we pre-registered that we would explore a suitable definition based on the questionnaire data.

To categorize participants and test this hypothesis, we conducted a principal component analysis (PCA) on five indicators of music-related behavior, including the importance of music in life, the extent of active listening, and the diversity of consumption formats. The first principal component (PC1) captured overall engagement with music: Higher scores indicated that music was more important to the participant, that they listened more actively, and that they consumed it across more formats. The second principal component (PC2) reflected differences in preferred consumption modes, with positive values indicating greater use of traditional ownership formats (e.g., CDs, vinyl) and negative values indicating heavier reliance on streaming. Because “lifestyle listeners” are, by definition, individuals for whom music is broadly integrated into daily life, we operationalized this category as participants with a PC1 score at least one standard deviation above the sample mean. This threshold identified those whose engagement with music was substantially higher than average, regardless of whether they preferred ownership formats or streaming. Based on this criterion, 152 participants (12.2%) were classified as lifestyle listeners, while all others were coded as non-lifestyle listeners.

The regression results shown in Table 7 suggest that lifestyle listeners differ significantly from those who are not classified as such when it comes to the informed song evaluation: they state on average 14-15 percentage points higher relistening probabilities (columns 1 and 2) and are willing to pay about 30 cents more for the music (columns 3 and 4). We find no evidence that the song evaluation of lifestyle listeners is affected differently by the information about AI-use than that of other listeners. In the between-subject analysis, the interaction effect between the AI and Lifestyle dummies is insignificant (columns 1 and 2). In the within-subject comparison, lifestyle listeners tend to decrease their song evaluation more strongly than others when they learn about the AI-origin of the song,

Table 7: The effect of AI use and being a lifestyle listener on informed relistening probabilities and WTP

	<i>Dependent variable:</i>					
	Again Info		WTP Song		Δ Again	
	(1)	(2)	(3)	(4)	(5)	(6)
AI	7.972*** (2.513)	7.816*** (2.515)	-0.018 (0.045)	-0.015 (0.046)		
Lifestyle	14.304*** (5.536)	15.020*** (5.545)	0.322*** (0.100)	0.327*** (0.100)	-0.363 (1.729)	-0.717 (1.770)
AI*Lifestyle	-1.717 (7.401)	-2.624 (7.398)	-0.302** (0.134)	-0.320** (0.134)		
Constant	37.077*** (1.781)	30.773*** (3.494)	0.426*** (0.032)	0.385*** (0.063)	-1.837*** (0.624)	0.390 (1.721)
Age groups	No	Yes	No	Yes	No	Yes
Observations	828	828	828	828	422	422
Adjusted R ²	0.026	0.032	0.010	0.013	-0.002	-0.006
F Statistic	8.367***	4.922***	3.898***	2.507**	0.044	0.479

Notes: OLS estimates based on the subset of participants who received information about the song's origin. In columns 1 to 4, we include observations from treatments HUMAN INFO and AI INFO, in columns 5 and 6, we restrict attention to observations from AI INFO. AI is a dummy variable indicating participants who listened to AI-generated songs. Pop is a dummy variable indicating that the song's genre was pop. Δ Again is the relistening probabilities stated after minus the one state before information about song origin was given. Regressions for columns (2), (4), and (6) include age group dummies. *p<0.1; **p<0.05; ***p<0.01.

but this effect is also not statistically significant. In contrast, the WTP for the song reacts more strongly to the information about AI-use. The effect of disclosing the AI-origin of the song is significantly more negative for lifestyle listeners: The effect is similar in size to the premium observed in lifestyle listeners on average, implying that the WTP for lifestyle listeners is similar to that of others for the AI-generated songs while they are willing to pay more for songs they are human-made. A possible explanation is that lifestyle listeners evaluate the listening experience largely independently of a song's origin, but react more strongly in monetary terms, perhaps because they place higher value on the human effort and authenticity behind artistic work.

Lastly, we hypothesize that participants' responses to the AI-origin information vary depending on whether they had previously suspected the song to be AI-generated. To investigate this hypothesis, we rely on the participant's stated likelihood of the song being AI-generated (*Prob_AI*) and a median split based on this variable, where below median probabilities were coded as 0 (low suspicion), and values above the median as 1 (high suspicion).

Table 8: Regression results for the correlation between assessed likelihood of AI use and change in relistening probability after information about AI use.

	<i>Dependent variable:</i>			
	Δ Again Info		WTP Song	
	(1)	(2)	(3)	(4)
Prob AI	0.044*	0.044*	-0.001	-0.002
	(0.024)	(0.025)	(0.001)	(0.001)
Constant	-4.646***	-2.494	0.498***	0.413***
	(1.652)	(2.257)	(0.084)	(0.114)
Age groups	No	Yes	No	Yes
Observations	422	422	422	422
Adjusted R ²	0.005	0.001	0.001	0.007
F Statistic	3.192*	1.097	1.217	1.611

Notes: OLS estimates based on the subset of participants who received information about the song’s AI-origin (treatment AI INFO). Prob_AI is a continuous variable representing the participant’s stated likelihood that the song was AI-generated. Δ Again is the relistening probabilities stated after minus the one state before information about song origin was given. Regressions for columns (2) and (4) include age group dummies. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

We observe that after learning the song was AI-composed participants with low suspicion decreased their relistening probabilities slightly more (mean -2.44) than those with high suspicion (-1.26), but the difference is not statistically significant ($t = -1.02$, $p = 0.310$). We further estimate a regression model where we regress the change in the relistening probability in response to the information treatment on the continuous variable *Prob_AI*. As shown in Table 8, the subjective likelihood of the song being AI-generated itself tends to increase the effect on the relistening probability (coefficient of *Prob_AI* of 0.044 , $p = .073$), which is in line with our fourth hypothesis that participants who did not expect the song to be AI-generated were more negatively affected by the information. While only significant at the 10%-level, this result suggests that the unmet expectation that a song was composed by a human can amplify the AI composer bias. For the monetary evaluation, however, expectations do not seem to matter, as the stated likelihood of the song being AI-generated does not affect the stated WTP for the song.

Auxiliary hypotheses We also tested two auxiliary hypotheses that are helpful in interpreting the above results and in gauging their implications for the music industry. First, we expected that participants would not be able to distinguish between AI-generated and human-made songs. Indeed, we found that participants were not able to accurately identify the source of the music. Participants were significantly more likely to assume that a song was AI-generated than human-made, but were typically not correct. They assigned even significantly higher probabilities of AI origin to human-made songs

(mean = 67.26) than to AI-generated songs (mean = 63.90, $t = 2.485$, $p = 0.013$). Second, we expected that participants who suspect music to be AI-generated or are informed of it will evaluate songs worse on average than those who do not suspect the use of AI. As reported above, we find that participants who were informed that the music was AI-generated showed significantly lower willingness to pay (WTP) for songs than those who did not know about the song’s origin (mean informed: 0.41, mean uninformed: 0.59, $t = 3.248$, $p = 0.0013$), but we cannot confirm that suspicion alone reduces WTP.

Among participants who received information about the song being of AI or human origin, only 18% altered their likelihood of relistening. Notably, these shifts weren’t confined to the AI-generated songs, but listeners exposed to human-created tracks also adjusted their preferences upon receiving information thereof. In treatment AI INFO, 72 participants (17.06% of the treatment group) changed their relistening probability, while in the HUMAN INFO treatment, the number was slightly higher at 77 participants (18.97% of the treatment group), but the difference is insignificant (two-sided test of equal proportions, $p=0.5336$).

Exploratory analysis of heterogeneous effects In an exploratory approach, we further investigate what determines whether and how participants want to adjust their relistening probability. First, we examine genre-based differences. Figure 7 shows that pop listeners who wanted to adjust their relistening probability after learning the song was AI-generated reacted somewhat more negatively than listeners of electronic dance music. However, the difference is not statistically significant (two-sided t-test, $p=0.1719$) and pop listeners were not more likely to adjust their relistening probability than listeners of electronic dance music (two-sided test of equal proportions, $p=0.9927$).

Next, we investigate heterogeneity with respect to the suspicion that the music may be AI-generated. We again use the binary classification of suspected AI use based on the median split in subjective probabilities introduced above. On average, those participants who had a high suspicion of the music being AI-generated adjusted their relistening probability more strongly downward (-22 percentage points) than those with no such suspicion (-8 percentage points), but the difference fails to reach significance in the small sample of 72 participants who wanted to change (two-sided t-test, $p=0.0808$).

Complementing this analysis of the role of beliefs, we then also analyze whether differing attitudes toward the use of AI in the music industry influence the effect of AI information. We split our sample at the median with respect to their support for using AI to create entire songs and analyze heterogeneity between those with above or below median levels of support. The result is maybe unsurprising but insightful: Participants who oppose the use of AI in full song creation are less likely to want to change their relistening probability after becoming informed about AI-use (two-sided test of equal

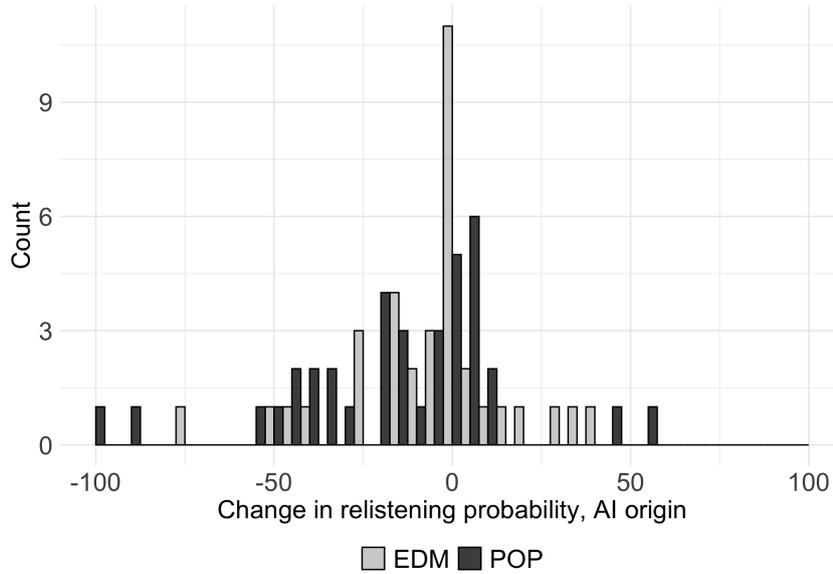


Figure 7: Histogram for observed changes in the relisteing probability (Δ Again), split by genre.

Notes: Δ Again is the relisting probabilities stated after minus the one state before information about song origin was given. Negative values indicate a reduction in the relisting probability after the disclosure of AI-use.

proportions, $p=0.0244$), but on average reduced their listening probability significantly more (-29 percentage points) in response to this information than those who are in favor of artists using AI (-1 percentage point, $p=0.0002$ in a two-sided t-test).

Exploratory analysis of WTP for streaming services Since streaming platforms account for 84% of sales in the U.S. music market (RIAA, 2025a), the implications of AI-generated music extend beyond individual song purchases to the streaming services themselves. Currently, streaming providers rely on artists to supply content, which is reflected in their cost structures. The rise of AI-generated music offers providers the opportunity to populate their platforms without paying artists, thereby potentially increasing revenues. The key question, however, is whether consumers would still be willing to pay for such a service, and if so, how much.

Participants generally reported a significantly lower willingness-to-pay for a streaming service offering only AI-generated music compared to a regular subscription (Regular: 4.22, AI-only: 2.61; $t = 7.27$, $p < 0.001$). Focusing on the AI-only subscription, we also find that information plays a crucial role: Informed participants in the AI INFO treatment reported a significantly lower WTP than those in AI NOINFO who received no information about the use of AI (Informed: 2.41, Uninformed: 3.01, $t = 2.05$, $p = 0.041$).

Regression analyses with the stated WTP for an AI-only streaming service as a dependent variable show that participants who had listened to an AI-generated song expressed

higher WTP, on average, than those who had listened to a human-made song, which parallels the results from the incentive-aligned WTP for individual songs. However, this difference disappears if we restrict attention to participants who were informed about the origin of the music. We further find that lifestyle listeners stated on average higher WTP for the AI-only streaming service, but they generally exhibit higher WTP for music, and this effect is apparently not reduced by prior exposure to AI-generated music. Expectations about AI use also correlate with willingness-to-pay: Participants who assigned a higher probability to their song being AI-generated reported on average higher WTP for an AI-only subscription. Detailed results are included in Table 12 in the Appendix.

These findings largely align with the findings on WTP for individual songs, but the effect of prior AI exposure for Lifestyle listeners vanishes and expectations appear to play a larger role in subscription choices than in one-off song purchases. Although these findings are based on a hypothetical scenario, they suggest that the valuation of a single song does not necessarily translate directly into subscription intentions.

Robustness Checks Since approximately half of our participants reported a WTP of zero for the song, the distribution is highly skewed and may raise concerns that our results are driven by the presence of these zero responses. To examine the robustness of our findings, we run two robustness checks, where (i) we re-estimated our analyses using only those participants who indicated a strictly positive WTP, and (ii) we estimate a Heckmann selection model.

First, when we analyze only WTP of participants with positive WTP, our insights regarding the general influence of AI origin and genre do not change substantially, but some differences emerge for the variables related to lifestyle listeners and expectations. Specifically, the interaction term for lifestyle listeners decreases notably in magnitude and loses significance, suggesting that among participants with a positive WTP, the origin of the song plays only a minor role for those classified as lifestyle listeners. In contrast, the effect of expecting the song to be AI-generated doubles in magnitude and becomes significant. This indicates that, within the subsample of participants reporting a positive WTP, expectations about the song’s origin play a more prominent role. The results are shown in Table 13 in the Appendix.

Second, we estimate a Heckman selection model that jointly models the probability of indicating a positive WTP and the amount stated conditional on paying to account for the large share of zero responses in WTP. The estimation results show that lifestyle listeners are significantly more likely to report a positive WTP, while frequent streamers are less likely to state a positive WTP. Conditional on a positive WTP, however, lifestyle status does not significantly influence the amount stated. But genre appears to be important: being a pop listener emerges as a significant positive predictor of WTP conditional

on it being positive. Importantly, the correlation parameter (ρ) is not statistically different from zero, indicating that selection bias is not a major concern in our data. The detailed results are included in Table 14 in the Appendix. Overall, the Heckman results corroborate the main findings and lend further confidence that our conclusions are not driven by the skewed distribution of WTP.

4 Discussion

The rise of AI and its impact on the creative industries initiated a heated debate about potential copyright theft when training the AI with unlicensed content (RIAA, 2025b)). A less discussed, but also very important, aspect is consumers’ acceptance of AI-generated content. Focusing on consumers’ preferences towards AI-generated music and the subsequent ethical challenges, we provide new insights from three studies. The results indicate that the industry is confronted with substantial challenges that we summarize in Table 9.

Table 9: Summary of our findings and their implications.

	Findings	Implications
Quality	AI-generated music is well perceived by consumers and AI will support artists in creating, producing, and distributing music.	<ul style="list-style-type: none"> • Transparency about AI labeling to ensure authenticity • Transparency about ownership to ensure information on the source of creation (right holders) • Transparency about input (training data) to avoid bias and stereotypes (based on AI training data)
Quantity	The widespread availability and usability of AI tools (e.g., MusicLM or Suno) results in lower market entry barriers for non-artists.	<ul style="list-style-type: none"> • Upload restrictions per account • Democratization of the Music Industry
Remuneration	<ul style="list-style-type: none"> • Risk of dilution of royalty pools. • Risk for streaming platforms as AI-generated music leads to lower willingness to pay. 	<ul style="list-style-type: none"> • Royalty model: Should AI-generated music be remunerated the same as human-made music? • AI-optimized targeting and cost-cutting potential by streaming services • Auditing mechanisms to ensure compliance

From a qualitative perspective, we find support that AI-generated music is well perceived by consumers. While, of course, some professionals argue that “[...] AI-

generated music is less creative and less genuine than music composed by human artists” (Rolling Stone Culture Council, n.d.), our results indicate that consumers care little about the difference between AI-generated and labeled music in comparison to human-made music, but consumers are affected by whether AI-generated music is being labeled as such.

This results in ethical implications for the industry’s stakeholders, as source transparency for AI-generated music is essential. This refers to labeling the use of AI in creating music to ensure authenticity (AI labeling). It also refers to the ownership of the rights for the song in order to ensure that the listener is able to determine the source of creation (ownership label). This aspect is important as new AI-based songs can be released by humans (e.g., a musician releases a new AI-based song along with her other human-made songs) or from an artificial band (e.g., The Velvet Sundown). In any case, informing customers about the rights holders of an AI-created song increases transparency helping to overcome ethical concerns. Research in platform contexts further shows that transparency on its own may not be enough if data practices are perceived as morally problematic; users’ trust depends at least as much on whether the underlying collection and use of data is considered ethically acceptable (Shah *et al.*, 2024). Furthermore, from a general perspective, source transparency is also important with regard to the input content to train the AI. Transparency in this dimension will help developing strategies to reduce biases and stereotypes in newly generated music in order to decrease the “more of the same” problem.

Moreover, our finding that customers perceive AI-generated music as a valid alternative to human-made music creates incentives for suppliers to flood the platforms with AI-generated music to secure a significant share of the royalty pool (quantitative perspective). This effect is boosted by the fact that the market entry barriers for new creators are very small (basically everybody can generate music using the current freely available tools) and that the creation of new music can be done automatically. As a consequence, a massive growth in the supply of AI-generated music is to be expected. Note that the quality of AI-generated music can be optimized with respect to user preferences, by monitoring and systematically evaluating user behavior. For example, when a streaming platform can observe that a song is skipped by many users after 20 seconds, it can use this information to adjust the song to reduce skipping and re-release an updated version of the song in a playlist. In this case, the AI-generated music is enriched with customer data to increase the quality of the song. However, user behavior can only be tracked in this way by the streaming-platforms, allowing them to use A/B testing “on the fly” and giving them a massive advantage for their own AI-based content.

In line with our finding that willingness-to-pay is lower for AI-generated music only streaming services, streaming services already restrict the number of uploads by suppliers.

Amazon, for example, has restrictions on the number of new digital content uploads per supplier segment to avoid being flooded with automated generated content (upload restriction). However, from an ethical point of view, the potential democratization of the music industry by allowing musicians and non-musicians (or even digital AI agents) to create new content is also an asset that may be diminished by platforms' commercial interests. [Rolling Stone Culture Council](#) (n.d.) asks “[...] how can we ensure that AI-generated music is ethical and respectful of human creativity? How can we prevent AI-generated music from displacing human artists and musicians?”. Our findings suggest that it is very important to ask these questions as the economic incentives are high.

The quantitative effect has further implications for the remuneration model ([Meyn et al., 2023](#)) as it will affect two dimensions of the royalty pool. First, assuming a constant size of the royalty pool, a large amount of new songs will dilute individual payments (long tail effects). Second, a large number of AI-generated songs potentially results in lower willingness to pay endangering the size of the royalty pool. These two effects have ethically relevant implications for the different stakeholders in the industry.

First, it is debatable whether AI-generated music should be remunerated the same as human-made music. On the one hand, consumers do not necessarily dislike AI based music, but on the other hand, streaming services only based on AI-generated music are considered less valuable according to our findings. Moreover, it is very likely that artists will themselves use AI in writing, composing, producing, and distributing music, blurring the distinction between “human made” and “AI-generated”. Thus, the question will be when a song has “too much AI” to be considered human-made. Under the European AI Act ([European Union, 2024](#)), which will be enforced from August 2, 2026, artists and platforms will typically not be required to label AI use, as disclosure becomes mandatory only for deep fakes; we believe all songs used in our studies would be exempt from the need to be labeled as AI-generated. Second, the strong position of global streaming services operated by Spotify, Amazon, Apple, and YouTube (Google) can also be used to optimize their AI based playlist management and to secure parts of the royalty pool by allocating AI based songs to top positions in playlists suggested by them to customer segments prone to listen to AI based music ([Pachali and Datta, 2025](#)). Given the substantial chances for streaming services to profitably use AI, the stakeholders in the industry should ensure that compliance to regulations are ensured by requesting auditing mechanisms to ensure transparency in the overall remuneration of content providers and the streaming service itself. Third, an ethically relevant aspect is how transparency towards consumers about not only AI-use, but also its consequences for musicians and industry would affect consumer preferences. Some sources (e.g., [Berger, 2024](#)) suggest educating fans about the consequences of AI use in music, as their streaming behavior importantly impacts the streaming based economy.

Given the high stakes behind the use of AI, the findings of our three studies imply a close monitoring of global copyright regulations is paramount for all stakeholders in the industry. In addition to establishing license agreements for training AI datasets (Berger, 2024), there is a substantial need to find agreements that specify clear terms and reflect a fair compensation of artists, labels, and streaming services – but also for creators of AI solutions. While artists have long embraced technology as part of their creative process, using AI for creativity alone will not prevent platforms from replacing them or AI systems from infringing on their copyrights. The focus must shift to robust licensing frameworks and enforcement mechanisms that protect artistic works from unauthorized use and ensure fair compensation. Additionally, fan education campaigns should emphasize the risks of unchecked AI proliferation in eroding the creative economy. In an environment where it will become increasingly unclear where AI was involved or not, artists disclosing details on AI use voluntarily could profit from doing so as they may be perceived by potential customers as more trustworthy or kinder. An empirical evaluation of a pay-as-you-go payment scheme by Regner and Barria (2009) suggests that customers reward kind suppliers with higher willingness-to-pay along the lines of a reciprocal kindness model (Dufwenberg and Kirchsteiger, 2004; Rabin, 1993).

While each of our studies relies on large quota-representative studies of the German population, the generalizability of our results to other countries and cultures may be limited. Specifically, our exploratory analyses suggest that individual views about how AI should or should not be used in music generation as well as listening habits and music preferences interact with valuations of AI-generated music. We expect these views and habits to be very different for instance in France or India so that perceptions of and the willingness-to-pay for AI-generated music may differ there.

Another limitation of our study is that we only provide insights into consumer valuations of AI-generated music and their WTP and discuss plausible implications for the development of the industry, but we cannot answer how the observed consumer reactions would actually change how musicians work or whether they experience their work differently and as more or less meaningful.

Declaration of generative AI and AI-assisted technologies in the manuscript preparation process

During the preparation of this work the authors used ChatGPT to address typographical mistakes, help with wording, debug R code and generate code for graphics faster. After using this service, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

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5 Appendix

Table 10: Distribution over age groups by treatment in Study 3

Age group	electronic dance music				Pop				Total
	AI		Human		AI		Human		
	Info	No Info	No Info	Info	Info	No Info	No Info	Info	
18-24	27	25	27	27	24	19	18	33	200
25-34	51	24	16	40	40	21	18	43	253
35-44	44	23	20	41	53	17	18	46	262
45-54	43	14	19	43	60	28	21	38	266
above 54	37	18	19	41	43	24	31	54	267
Total	202	104	101	192	220	109	106	214	1248

Table 11: Loading table of PCA analysis

	PCA1	PCA2	PCA3	PCA4	PCA5
Important	0.594	-0.202	-0.188	0.189	-0.732
Active	0.573	-0.131	-0.293	0.351	0.667
Listen Phy	0.320	0.594	-0.361	-0.643	0.022
Listen Dig	0.290	0.607	0.661	0.333	-0.015
Listen Stream	0.364	-0.470	0.559	-0.562	0.137

Notes: Loadings of the first two principal components. *Important:* How important music is to the participant (7-point Likert scale). *Active:* percentage of time participant spends listening to music actively, as opposed to passively. *Listen Phy, Listen Dig, and Listen Stream:* Number of hours participants spend listening to music from physical media (e.g., CDs), owned digital copies, and paid streaming services, respectively (past 7 days).

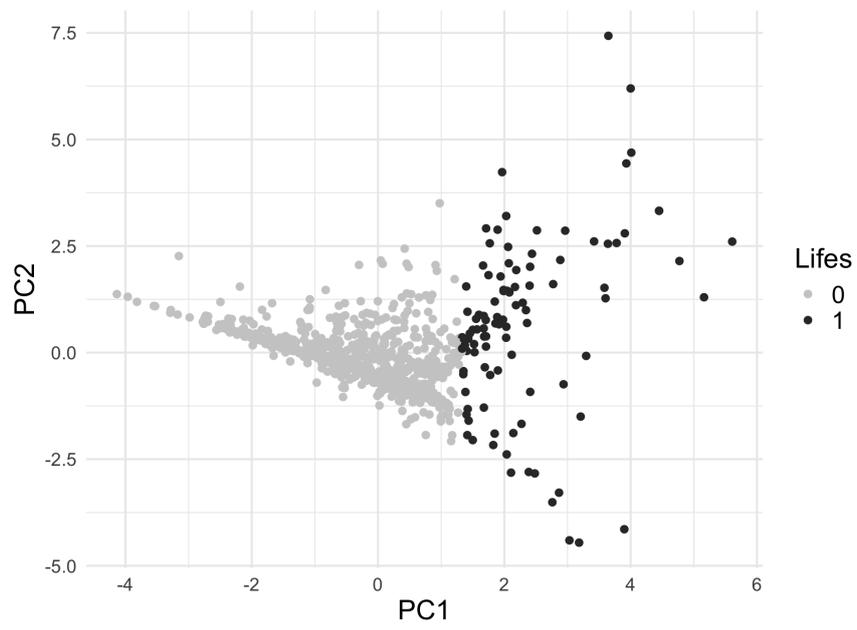


Figure 8: Scatterplot PCA analysis

Table 12: The effect of song origin, the information about it, genre and being a lifestyle listener on WTP for a hypothetical streaming service offering only AI-generated music.

	<i>Dependent variable: WTP Spotify AI</i>			
	(1)	(2)	(3)	(4)
AI	0.994** (0.431)	-0.122 (0.406)	-0.264 (0.297)	
Info	0.128 (0.377)			
AI*Info	-1.290** (0.528)			
Pop		0.099 (0.401)		
AI*Pop		-0.307 (0.562)		
Lifestyle			1.665** (0.656)	
AI*Lifestyle			-0.500 (0.874)	
Prob AI				0.012** (0.006)
Constant	3.472*** (0.407)	3.526*** (0.458)	3.295*** (0.413)	2.662*** (0.545)
Observations	1,248	828	828	828
Adjusted R ²	0.039	0.018	0.030	0.024
F Statistic	8.207***	3.175***	4.638***	5.030***

Notes: Column 1 uses the full sample. Columns 2–4 use only observations from the informed treatments. All specifications include dummies for age groups. *AI* is a dummy taking the value 1 if the participant listened to an AI-generated song. *Info* is a dummy that takes the value 1 if the participant received information about the song being AI-generated or human-made. *Pop* indicating that the song's genre was pop. *Lifestyle* is a dummy that takes the value 1 for participants classified as lifestyle listeners. *Prob AI* denotes the participant's stated likelihood that the song they heard was AI-generated. *p<0.1; **p<0.05; ***p<0.01.

Table 13: The effect of song origin, genre, and being a lifestyle listener on WTP for the song in an informed subsample that stated a positive WTP.

	<i>Dependent variable: WTP Song</i>			
	(1)	(2)	(3)	(4)
AI	-0.077 (0.061)	-0.140 (0.087)	-0.061 (0.065)	
Pop		0.020 (0.086)		
AI*Pop		0.122 (0.121)		
Lifestyle			0.204* (0.122)	
AI*Lifestyle			-0.090 (0.179)	
Prob AI				-0.004* (0.002)
Constant	0.819*** (0.083)	0.820*** (0.093)	0.783*** (0.085)	0.902*** (0.174)
Observations	394	394	394	198
Adjusted R ²	0.011	0.013	0.015	0.031
F Statistic	1.896*	1.756*	1.862*	2.275**

Notes: OLS estimates. Sample is restricted to the informed participants stating a positive WTP. All regressions are controlled for age. AI and Info are dummy variables indicating whether the song was AI-generated (versus human-generated) and whether the participant received information about the song's origin, respectively. Pop is an indicator for the assigned genre, while Lifestyle is a dummy for whether a participant was flagged as a lifestyle listener. Prob AI denotes the participant's stated likelihood that the song they heard was AI-generated. *p<0.1; **p<0.05; ***p<0.01.

Table 14: Heckman Selection Model (WTP for Song)

	<i>Tobit-2 (Heckman) Model</i>	
	Selection: Pr(WTP Song > 0)	Outcome: WTP Song
Intercept	0.281 (0.161)	0.915*** (0.170)
Listen Stream Paid	-0.012** (0.004)	
AI	0.052 (0.072)	-0.053 (0.049)
Pop	-0.115 (0.075)	0.121* (0.053)
Lifestyle	0.286* (0.123)	0.101 (0.074)
Prob AI	0.001 (0.002)	0.000 (0.001)
σ		0.612*** (0.029)
ρ		-0.188 (0.313)
Log-Likelihood	-1426.224	
Observations	1246 (613 censored, 633 uncensored)	

Notes: Maximum-likelihood Heckman (Tobit-2) selection model. Outcome is the WTP amount conditional on WTP begin positive; selection equation models the probability of any positive WTP (probit). Standard errors in parentheses. All specifications include age-group controls (coefficients omitted). Listen Stream P is the hours per week they spend listening to paid streaming services. AI indicates AI-generated (vs. human) song. Lifestyle is the lifestyle listener indicator. Pop is the dummy for pop music. Prob AI is the respondent's stated probability that the song was AI-generated. *p<0.1; **p<0.05; ***p<0.01.