"The Effect of AI Content Labels on Music Consumption and Marketing"

Gianni Livigni

Mentor: Manuel Cherep, MIT

Abstract

This study investigated how labeling music as AI-generated influences listener perceptions, engagement behavior, and whether such effects vary across attitudes toward AI. Fifty-two participants completed an online survey in which they rated and evaluated both AI-generated and human-composed songs before and after AI-authorship labels were introduced. Each participant rated twenty songs (five AI, five human on each part) across two conditions, providing both quantitative ratings and qualitative feedback explaining their evaluations. Paired-samples t-tests revealed that labeling significantly reduced both ratings ($p < .001$) and playlist-add intentions ($p = .002$) for AI-generated songs, while human song evaluations remained stable ($p = .440$). An additional comparison showed that the rating gap between AI and human songs widened after labeling ($p = .044$), indicating that transparency about AI authorship magnifies authenticity bias. An independent-samples t-test showed that participants who were positive toward AI were generally more receptive ($p = .011$), yet a mixed ANOVA found no significant interaction between label effect and attitude group ($p = .982$), suggesting that labeling impacted both groups similarly. Qualitative responses reinforced these results: participants described AI music as “mechanical,” “soulless,” or “lacking emotion,” while human songs were praised for “authenticity” and “connection.” Overall, the findings demonstrate that while transparency through labeling supports ethical clarity, it simultaneously shapes perception and behavior, reducing appreciation for AI-generated music regardless of attitude. These results highlight the complex role of disclosure in the age of algorithmic creativity.

1. Introduction

In June 2025, a band known as The Velvet Sundown appeared on Spotify and social media platforms, gaining hundreds of thousands of followers (Relevant). Their popularity grew among both fans and speculators. Many took to their platforms to share the new "hidden gem" band they discovered, while others grew skeptical and began investigating the group (jesealee). Many openly accused the band of being entirely AI-generated; their social media posts, album art, and especially the music itself (musictmwindow). Later that month, the person behind the project made a post on their Instagram account, clarifying it as an "ongoing artistic provocation designed to challenge the boundaries of authorship, identity, and the future of music itself in the age of AI (Bellucci 2025)." Many felt betrayed, while others viewed the stir as a significant milestone in music history, marking the transition from human artists to artificial algorithms (legallyfallon_, musicnewsblitz).

One of the primary reasons people reacted so negatively to The Velvet Sundown was that there was no explicit indication to the listener whether the music was AI-generated or not. The lack of labels on products negatively impacts both parties involved in any transaction. Consumers can be harmed or get something they did not want; furthermore, if they find out about these "hidden characteristics," the seller's integrity and the consumer's trust in them are hindered (Pick). On top of this, a lack of labels might incentivize a consumer to stop purchasing altogether ("Lack of information, poor product top reasons for abandoning purchase"). A good example of this is in the food industry. Without clear labels, buyers are led to make general assumptions of the product based on other less impactful factors, such as the quality of the label or container that the food is in, potentially leading them to purchase something that they do not want to (USDA, NSF). This gap in a transaction is referred to as asymmetric information, one party knowing critical information about a product that the other does not. (Boyle). Ultimately, the more transparency there is between consumers and retailers, the more both parties can focus on making intentional, careful, and reliable decisions that align with what they want and their morals.

The introduction of the internet and its entwining into everyday life made labels even more important. Many experts predict that the spread of misinformation will get worse in the future. The media now appeals more to emotion than facts (Anderson and Rainie 2017). This has led platforms such as Twitter to create labels to inform users if posts may contain misleading or

false narratives (Polny, n.d.). The majority of Americans support labeling media on the internet (Straub). In all, research has made it clear that labels on the majority of content on the internet are necessary (Sharot and Kelly 2024).

There is no difference when it comes to music. A great example of this is explicit content labels, which were introduced in 1985. Record companies work with artists to decide whether or not a project contains explicit themes or lyrics. If so, a clear label, suggesting "parental advisory; explicit content," is placed directly on the album cover. This label was born from unclear information, as parents pushed for its implementation due to their concern for their children listening to music about mature themes (Jackson, n.d.). These labels made their way to streaming platforms once the internet came, a clear "E" on any music that may need to be reviewed before children listen to it. Labels such as these exist as informational and ethical safeguards, helping consumers make the most informed choice they can.

2. Review of Literature

2.1. Pushback of Technology in Music and the Importance of Regulation

Music is a medium that is driven by innovation. From the baroque movement to contemporary, each album, piece, song, demo, and era represents something unique in humankind. A major shift that has been observed in music over the past three centuries has been technology's effect on this innovation. Technology has a great influence on every market; however, inventions such as the microphone, radio, CD, and more have completely reinvented how people interact with music (Sandal, n.d.). The most important part of this vast history has been the digital age of music.

The innovations that emerged out of the digital age changed the game for music, for better and for worse. One boon of this new technology was that music became exponentially more accessible to write, produce, and publish. Anyone with a device and an internet connection is now able to create their vision for music. For instance, songs such as "Cross" by Justice and "Umbrella" by Rihanna were made in GarageBand, an app for iOS devices (Quora, n.d.). Before this, artists would need an expensive instrument, costly hours of studio recording time, and a record label to publish their music. Another benefit that came with the digital age was social media. The accessibility and authenticity of social media allow artists to find an audience for their music without the need for a label deal or busking. On top of this, artists are now able to use

this platform to connect directly to their fans, instead of going through a PR team to do the same thing ("The Impact of Technology on the Music Industry" 2021). These benefits paint the digital age as a revolution, making music accessible for all to create and appreciate. However, these developments are dwarfed by the complicated and revolutionary introduction of the streaming era.

The streaming era was a direct result of the regulations in the digital age. The revolution began when file-sharing service Napster was founded in 1999, and while it was not the first of its kind, it became infamous for giving over 60 million users access to downloading music for free, albeit illegally. This practice was a game-changer for music fans. Suddenly, millions of hours worth of music were available to anyone with a computer and internet access. With pirating software such as Napster taking over the digital market, governments and big industry names were forced to scramble to find a solution and give artists the kickback they deserve (Lamont and Pynchon 2013). After being sued by not only the federal government but also several big-name record labels and artists, including but not limited to A&M Records, Metallica, and Dr. Dre, Napster was officially dismantled in March of 2001 ("The death spiral of Napster begins | March 6, 2001 | HISTORY", n.d.). While this was going on, the industry was searching for a way to scratch the instant-satisfaction itch that Napster provided, while still operating within national copyright laws. The first to attempt this was Apple, with the launch of iTunes in early 2001, followed by the iPod, an ultra-portable MP3 player. While nowhere near as convenient or cost-effective as its predecessor, it was still a proposed solution to the hole Napster left in its wake ("Apple launches iTunes, revolutionizing how people consume music | January 9, 2001 | HISTORY" 2019). More potential solutions were raised, such as services like Bandcamp and Tidal.fm; however, none truly succeeded like how Spotify did in 2008. With high-quality audio, a subscription-service-based platform, and personalized recommendations made Spotify the standard for listeners around the world (EN, n.d.).

Without the intervention of copyright laws and legal frameworks, piracy would have continued to dominate, leaving artists and labels uncompensated for their work. At the same time, the very regulations that dismantled platforms like Napster created an environment in which legal streaming services could thrive. However, these solutions also revealed new flaws, as the bulk of the profits went to corporations and platforms rather than to the artists themselves (NCEG, n.d.). Nevertheless, the streaming era has divulged one crucial thing about the music

industry: innovation needs regulation. Balanced and proper rules must be established to prevent exploitation of consumers, artists, and companies.

2.2. Growth of AI-Generated Music and Ethics in the Music Industry

Similar to how the digital age liberalized the process of songwriting and publishing, the AI generation has created even more readily available ways for people to create the music they want. With the constant expansion and innovation in the artificial intelligence market, AI music generation is becoming more accessible, affordable, and of higher quality. Tools such as Suno.com, ILoveMusic.ai, and others enable users to create music by simply describing what they want to hear, eliminating the need for prior knowledge of music theory, instrument proficiency, or industry connections (Soundful).

Several factors distinguish the ethical debate surrounding AI from previous advancements in music, including arguments about authorship, originality, and fairness. Many argue that AI-generated works lack the emotional depth, cultural context, and lived experiences that define human creativity. Critics argue that AI-generated music sounds hollow and falls short in communicating the intricate emotion that human-made music possesses (Rolling Stone). Others see AI as another new tool, similar to digital synthesizers or production software, that expands artistic possibilities and accessibility. After all, the music industry is fueled by innovation (Lee). "Ghost artists have been part of music culture for generations, and AI is only the newest tool in that lineage," says Ben Camp, a professor at Berklee College of Music (Bellucci 2025). Ethical concerns also include copyright and ownership: who deserves credit and royalties for a song generated by a machine trained on human-made music? Furthermore, there is the risk of exploitation, as labels or companies may prioritize AI tracks to cut costs, reducing opportunities for human musicians.

The most troubling part of the ethical debate has been the nonconsensual use of AI recreations of artists' voices in music. Several AI programs have been developed that can artificially recreate famous vocal profiles. From light-hearted covers to full-on AI artist tours, the technology for vocal recreation has seen an alarming rate of growth. Many have concerns about the implications the use of these programs has on personality rights, morality, copyright, and even the role of artists in the future (Joseph and Khemka, n.d.). In an interview with ABC News in 2023, artist SIXFOOT 5 developed a song using AI recreations of Adele's vocals. Instead of

releasing it, he planned to send it to Adele himself, as proof of concept for how vocalists' jobs may be in the future. He notes, "I think artists should be more afraid because I could see the music industry saying, 'We don't really need you anymore. We have your vocal profile (Smith, Lippiello, and Pereira, n.d.).'" The most concerning group of these covers is the ones that utilize AI to replicate the likeness of artists who have passed away. Artists such as Chester Bennington from Linkin Park and Chris Cornell from Audioslave have had their voices used on the internet on music covers. One cover, with Chester's voice singing Gotye's "Somebody That I Used To Know," gained over 2.2 million views on YouTube (Gupta 2024). There are many people who argue that the use of these artists' voices is immensely unjust. Nevertheless, these covers continue to flood the internet.

Currently, national law is not prepared for these covers to hit the market. If an artist uses an AI voice in their own written song, who owns the song? Who gets paid the royalties? Should it be illegal to use someone's voice when they are unable to consent to it? These are concerns that have yet to be researched, for legality and morality.

Regulation has yet to hit AI in music like it has with MP3 pirating or sampling years ago. However, until the industry knows what exactly the consensus is on the ethics of AI and music, the potential impact of these labels cannot be predicted accurately.

2.3 The Velvet Sundown and AI Labeling

The Velvet Sundown made waves in the music community. One of the biggest concerns was that no one knew for sure if the band was AI-generated or not before the creator clarified it on social media. Currently, Spotify, the leader in music streaming, permits AI tools for music and provides no labels for listeners to know if a song or artist is AI-generated or not (Sarmiento). This leads to listeners using recognition skills to deduce if an artist used AI. However, many industry experts predict that in the near future, these attempts may be futile. AI technology advances at an exponential rate (Chang 2025). In a year, AI music may be indistinguishable from "real" music. Furthermore, the difference between AI-generated, AI-assisted, and completely human-composed music is still very blurry (Bellucci 2025). All of these factors make it hard for consumers to filter out what they want or do not want to listen to.

Progress is being made, however. Sophie Jones, the chief strategy officer at the music trade body the British Phonographic Industry (BPI), is pushing the UK government to mandate

transparency with AI companies. Currently, there is no data supporting whether or not these labels will help consumers align their listening with their beliefs, or if they would help distributors present music using these AI tools to the right audience (Sarmiento).

3. Hypothesis

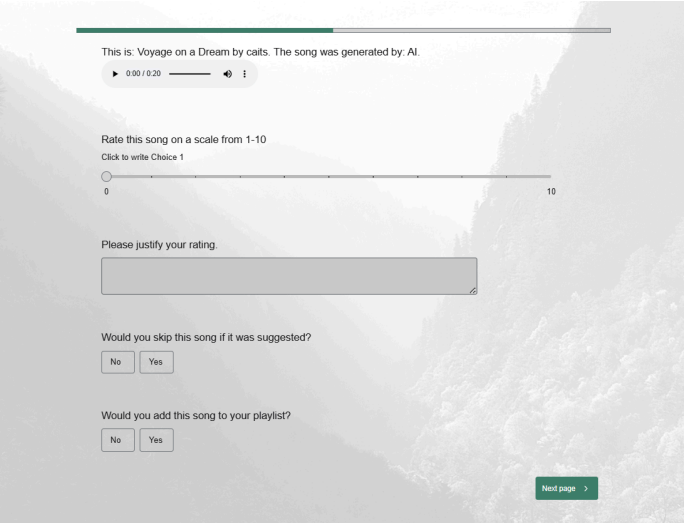
The study put in place two hypotheses to see if AI-generated labels would help both listeners and distributors on streaming platforms. These hypotheses were implemented to help organize and categorize the data that would be collected later.

1. AI content preferences will help listeners align their music listening with their true preferences regarding AI-generated/assisted music.
2. AI content preferences will help music marketers align AI-generated/assisted music with an audience that will appreciate it more.

4. Methodology

4.1 The Survey

This study involved a survey that was created, distributed, and filled out online using Qualtrics. This survey was determined to be exempt by the IRB at Couhes MIT. Participants were given a link to the survey, which contained four parts: Preliminary questions, Test 1, Test 2, and additional questions.



Test 2 example, created by student researcher using Qualtrics, 2025

The preliminary questions asked participants as well as 3 questions about their previous experiences and thoughts on AI music, with answers provided in response to three questions: either “Yes” or “No.” After this, participants were given two tests. In Test 1, users were in sequence given 10 20-second clips of songs, 5 AI-generated and 5 human-composed. These songs were curated through a set of criteria to ensure their quality, obscurity, and originality.

Curation Criteria:

Human-made music:

Soundcloud -> Genre

Curation Criteria:

Artist has <100,000 listeners

If there are lyrics, they must be in English

Songs are not experimental and fit the genre well

No producer tags (sounds that mark the song was made by a certain artist)

Songs have names and credited artists

The artist's page shows that the artist is human

AI Music:

Suno -> Genre

Curation Criteria:

Not themed around internet culture or AI

If there are lyrics, they must be in English

If there are vocals, they must sound convincing (no tinny breaks)

Genres:

Electronic Dance

Funk

Pop

Hip-Hop

Rock

There were 5 music genres across all of the songs. In each test, there was 1 AI-generated and 1 human-composed song from each genre. After listening to the clip, the participants were asked to rate the song on a scale from 1 to 10 and justify their choice in a short-answer question. They were then also asked two yes or no questions, one asking whether or not they would skip the song and one asking if they would add it to a playlist. After this, they were given Test 2, identical to the first, except with new songs, and each song came with a label distinguishing whether the song was AI-generated or human-composed. Following these two tests, the participants were given 6 questions to answer about their future preferences with AI music on streaming services.

4.2 Sample and Data Collection

From October 5, 2025, to October 19, 2025, a link for a survey was distributed by researchers through emails, online posts, and outreach to field specialists, including participants from SiriusXM, Berklee College of Music, and more. Participants were given a short description of the purpose of the study and a link to complete the survey. A total of 103 anonymous responses were collected. After filtering for unfinished and invalid responses, 52 data points were used for testing.

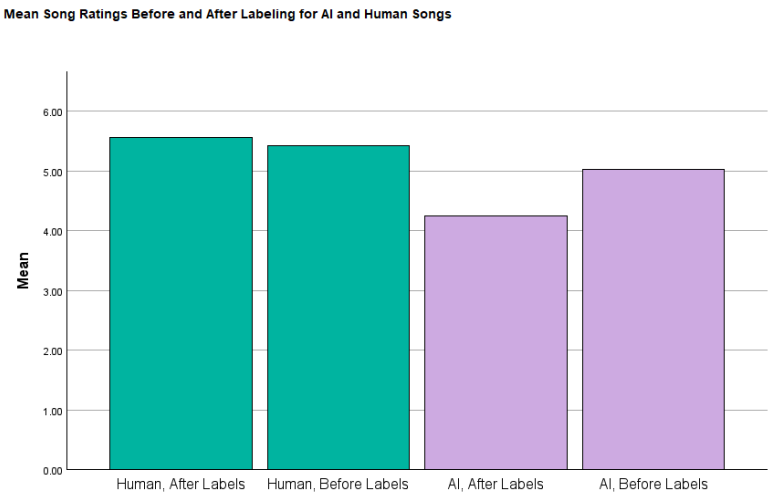
4.3 Data Analysis

For Hypothesis 1, three paired-samples t-tests were used to examine whether labeling music as AI-generated would affect participants' perceptions and behaviors. The first t-test compared the means of AI-generated song ratings before and after labeling, while the second compared the playlist behaviors of participants before and after labeling. Finally, a paired samples t-test examined the difference between the mean ratings of human and AI-generated songs before and after labeling. For Hypothesis 2, an independent-samples t-test and mixed ANOVA test were used. The independent-samples t-test compared responses between two attitude groups: participants who believed AI-generated music should be allowed on streaming platforms ("AI-positive") and those who did not ("AI-negative"). The mixed ANOVA was designed to determine whether the effect of labeling (before vs. after) interacted with participants' overall attitudes toward AI music. Lastly, qualitative trends were analyzed on the responses to the "Justify your rating" questions under each song. All tests and graphs were conducted using IBM SPSS.

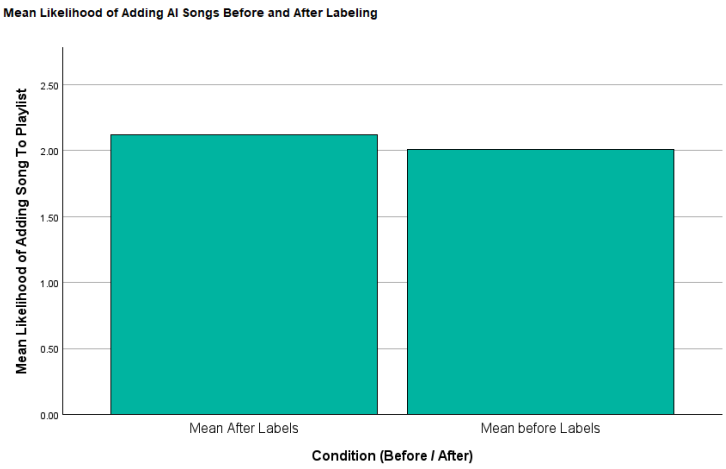
5. Results

5.1 Hypothesis 1

Hypothesis 1 examined whether labeling a song as AI-generated would influence participants' perceptions and behaviors toward the music. Two paired-samples t-tests were conducted to test this hypothesis. The goal of the two t-tests was to examine whether participants' ratings and playlist behavior changed after learning which songs were AI-generated. The first compared participants' mean ratings of AI-generated songs before and after labeling. The one-sided p-value was < .001, and the two-sided p-value was < .001, indicating a statistically significant decrease in ratings once



Created by student researcher using IBM SPSS, 2025



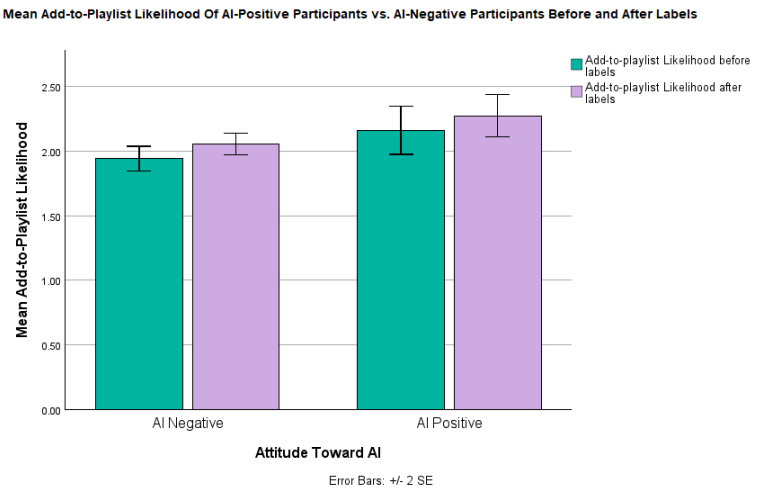
Created by student researcher using IBM SPSS, 2025

participants were informed that the songs were AI-generated (M = 0.76). The second test compared participants' playlist behaviors before and after the labeling. The means of how often participants answered "Yes" to the question, "If this song was suggested to you, are you likely to add it to your playlist?" were compared. The one-sided p-value was <.001, and the two-sided p-value was <.002, indicating a statistically significant change in playlist-add behavior. The mean difference was –0.115 (M = –.11538), showing that participants were less likely to add AI songs once they were identified as AI-generated. Finally, another test examined a potential difference between the mean ratings of AI and human songs before and after labeling. After labeling, AI song ratings significantly decreased (p = .044 two-tailed, .022 one-tailed), while human song ratings slightly improved with a highly significant difference (p < .001).

These results demonstrate that labeling not only reduced participants' subjective ratings of AI music but also decreased their behavioral willingness to engage with it, both supporting hypothesis 1.

5.2 Hypothesis 2

Hypothesis 2 examined whether the effects of labeling differed between participants with positive versus negative attitudes toward AI music.

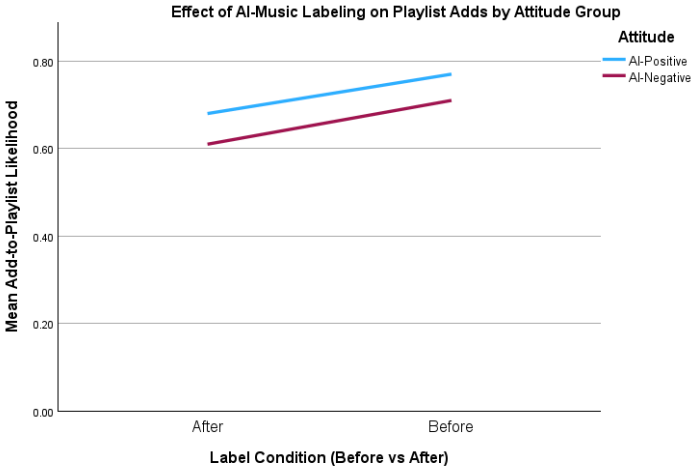


Created by student researcher using IBM SPSS, 2025

An independent sample t-test was conducted to determine whether AI-positive and AI-negative participants differed in their willingness to add songs to their playlists after labeling. The test grouped participants into two

categories based on their response to the question, “Do you believe AI music should be on streaming platforms?” Participants who answered “Yes” were categorized as AI-positive, while those who answered “No” were categorized as AI-negative. Mean “add to playlist” scores for each group were compared. Assuming equal variances, the one-sided p = .005 and two-sided p = .011. When variances were not assumed equal, the one-sided p = .013 and two-sided p = .026. All were below the .05 significance threshold. AI-positive participants were significantly more likely to add AI-generated songs to their playlists compared to AI-negative participants. This supports Hypothesis 2, showing that overall attitudes toward AI influence behavioral responses to AI-generated music.

To further test whether labeling effects differed between these attitude groups, a two-way mixed ANOVA revealed a significant main effect of AI music labels, $F(1, 49) = 8.593$, $p = .005$, $\eta^2_p = .149$, indicating that labeling significantly changed whether or not participants would have added AI songs to their playlist overall. There was also a significant main effect of AI Attitude, $F(1, 49) = 7.563$, $p = .008$, $\eta^2_p = .134$, showing that AI-positive participants were generally more willing to add AI-generated songs. However, the interaction effect (Label × AI Attitude) was not significant, $F(1, 49) = 0.001$, $p = .982$, $\eta^2_p = .000$, indicating that the labeling effect was similar for both groups. Labeling decreased overall willingness to add AI-generated songs, but this reduction was not significantly different between AI-positive and AI-negative groups. While attitudes toward AI influenced general preferences, they did not judge the labeling effect itself.



Created by student researcher using IBM SPSS, 2025

5.3 Qualitative Findings

For each rating participants gave, they were asked to justify their rating in an open-ended question. Manual analysis of all 520 answers revealed eight recurring themes. The percentage of these themes was calculated in the answers. Then, a general trend was drawn from both manually analyzing the data and from how much each theme was presented.

Theme	Definition	Trend	% Shown AI	% Shown Human
Authenticity / Soul	Mentions of human, real, or emotional quality	Dominant in Human songs	9.6	11.9
Artificiality / Robotic	References to mechanical, synthetic, or fake sounds	High in AI songs, especially after labeling	8.8	3.8
Emotion / Engagement	Descriptions of connection or emotional impact	Strongly linked to higher ratings	6.5	6.5
Production Quality	Technical comments on mixing, polish, or balance	Common in both AI and Human songs	4.2	3.8
Bias / Label Awareness	Statements explicitly noting a change after seeing the label	Strong evidence of labeling influence	0	0
Novelty / Curiosity	Mentions of originality or creativity	Often positive for AI songs	4.2	3.5
Generic / Template	Comments about repetition or formulaic sound	Negative, frequent in AI tracks	6.2	2.7
Genre Fit	Comments about personal bias regarding the genre of the song	Prominent in both types of songs	19.2	22.7

From this, it is shown that “Artificiality” and “Bias Label” codes were far more frequent in AI responses, while “Authenticity” and “Emotion” dominated Human songs. Additionally, comments about the genre were relatively common in both types of songs.

6. Discussion

This study examined how labeling AI-generated music influences listener perceptions and behaviors, and whether such effects vary across audience attitudes. AI-music labels had a significant impact on ratings and whether or not participants would have added music to their playlist. However, there were no significant differences between AI-positive and AI-negative groups. These results reveal that labeling impacts individual reactions more than it distinguishes audience segments.

From testing Hypothesis 1, the data show that people rated and engaged with AI music less positively after being told it was AI-generated. This suggests that awareness of AI authorship triggers bias or skepticism toward authenticity and emotional depth. This reinforces the idea of "authenticity bias" in media, or the idea that people value the human creation behind a piece of art (Levy and Bailey 2022). In this case, once participants were aware of the inorganic origins of the song, their feelings towards it were immediately hindered. Similarly, the labels affected the participants' reactions to human music as well. Human music was generally rated higher once labeled, while AI music was rated lower with labels. These findings could underline a bias that humans have towards AI and computer-generated media in general. A psychology study in 2015 found that many people experienced "source effects:" they trusted information less when they knew it came from an algorithm than when they knew it came from a person. Furthermore, participants were less likely to add AI-generated songs once they were identified as such, reflecting a similar pattern in behavior. Qualitative responses further echoed this trend, with participants describing AI songs as more 'robotic' and 'soulless' after labeling, while human songs were associated with 'emotion' and 'authenticity. While the labels were good at informing consumers ethically, they inadvertently reduced their appreciation for the AI-generated music. Further testing should explore whether consumers enjoy having the option to see these labels.

The most intriguing part of the results was the lack of effect that labeling had on AI-positive and AI-negative respondents. When testing Hypothesis 2, it was shown that labeling did not reveal or highlight different groups that were more open or closed-minded toward AI music. While this challenges the hypothesis, it supports another argument discussed in the paper: that the exact opinions people have about AI are still up for debate. Although AI-positive participants were generally more open to adding AI songs, the Mixed ANOVA showed that

labeling affected both groups similarly ($p = .982$), suggesting that preexisting attitudes did not change how labeling shaped behavior. Whether or not people enjoy, appreciate, or are taken aback by AI music is more nuanced than a simple "you love it or you hate it." This decision can come from a multitude of factors, such as the quality of the output, how much it appeals to their specific taste, and musical styles. This is a sound explanation of the culture of music, as even different genres have sub- and micro-genres.

The broader implications of this study are clear. Label transparency is undoubtedly important, for ethical and practical reasons. However, the lack of correlation with AI-positive and negative groups implies that labels concerning AI in music have to be studied further. Music marketers and distributors should invest in more research concerning labels before fully implementing these labels. Creators should still focus on emphasizing transparency when creating and communicating with their fanbases. While the study's findings highlight the need for clarity and full disclosure in the realm of music, it also introduces measurable perceptual and behavioral biases against AI-created art.

The applications for these findings are not limited to music, either. With the availability of technology such as Sora AI, the ability of a common person to distinguish AI-generated and human-made media is dwindling day by day. It will not be long before this content will be used to incriminate people, spread false narratives, and feign artistic talent. While it is evident that labels are vital to the sanctity of genuineness on the internet, they are not foolproof. AI media generator sites apply their own watermark, but workarounds are already being developed. Within weeks of Sora AI's public release, multiple websites popped up with an easy way to remove the watermarks.

However, many solutions are already prepared to be deployed. AI tags baked into the media's code can keep track of what content is AI-generated even without a visual or audio label. Restrictions on the use of generators and limitations on their use are also being implemented. Select words and prompts that could be used to spread hateful or misleading rhetoric are banned from the site.

Nonetheless, the most powerful weapon against media ambiguity is legislature. Federal restrictions on using AI-media for nefarious or inauthentic purposes deter a large number of people because of the potential risks that breaking federal law poses. Additionally, laws making transparent labels for AI content will make using AI for these purposes harder to do legally. They

can also help people make informed decisions on where they get their information and media, just like necessary explicit content labels. The government ultimately has the most important role in ensuring that people know what media they are consuming.

The limitations of the study include the sample size, length, repetitiveness of the survey, and more. Firstly, the limited sample size of 52 limits the generality of the results. Repeating similar tests for the survey could have also affected the results, as participants could have gotten too familiar with or grown uninterested in the survey. Furthermore, the length of the survey could have affected whether or not respondents finished the survey or not. Lastly, the way that different genres were presented in the survey could have impacted the results. A reworked survey could allow participants to listen to music within a genre of their choice, better reflecting the opinions they have of AI and human-generated music.

Future research should focus on labeling music using AI in more detail, rather than in a binary state. For example, labels can include descriptions such as “AI-assisted,” “AI-inspired,” and more. This would explore the extent of the bias in the labels on consumers. Furthermore, this could lead to more discoveries on how transparent artists should be with their audience. If AI were displayed as less of a cheap and unoriginal way to make music, and more as a tool to expand creativity, listeners could be more open to experiencing music, and even other media that uses AI.

Bibliography

Anderson, Janna, and Lee Rainie. 2017. “The Future of Truth and Misinformation Online.” Pew Research Center. https://www.pewresearch.org/internet/2017/10/19/the-future-of-truth-and-misinformation-online/.

Bakare, Lanre. 2025. “An AI-generated band got 1m plays on Spotify. Now music insiders say listeners should be warned.” The Guardian. https://www.theguardian.com/technology/2025/jul/14/an-ai-generated-band-got-1m-plays-on-spotify-now-music-insiders-say-listeners-should-be-warned.

Bellucci, Tara. 2025. “The Velvet Sundown: The AI Band Controversy Explained.” Berklee College of Music. https://www.berklee.edu/berklee-now/news/velvet-sundown-ai-band-controversy.

Boyle, Michael J. n.d. “Asymmetric Information in Economics Explained.” Investopedia. Accessed August 9, 2025. https://www.investopedia.com/terms/a/asymmetricinformation.asp.

Chang, Ellen. 2025. “How fast are AI companies evolving? Check this out. | Institute for Business in Global Society.” Harvard Business School. https://www.hbs.edu/bigs/perplexity-aravind-srinivas.

Eastwood, Brian. 2023. “How should AI-generated content be labeled?” MIT Sloan. https://mitsloan.mit.edu/ideas-made-to-matter/how-should-ai-generated-content-be-labeled.

French, Carly. n.d. “Listening to the Customer: Leveraging Preferences in Marketing.” Spiceworks.

jesealee. n.d. “Is this band real?” TikTok post provoking discussion about The Velvet Sundown before they confirmed they were AI. https://www.tiktok.com/@jesealee/photo/7521023862130101534?_r=1&_t=ZP-8zXv89i1s0k.

“Lack of information, poor product top reasons for abandoning purchase.” n.d. Retail Customer Experience.

Lee, Edward. n.d. “AI and the Sound of Music.” The Yale Law Journal.

legallyfallon_. n.d. “tough look for us,” TikTok post, "me and my boyfriend vibing to thing song 100 times before realizing it was AI". www.tiktok.com/@legallyfallon_/video/7522135932846345503?_t=ZP-8zXxSedPX1r&_r=1.

musicnewsblitz. n.d. “Ai Music will ruin the industry 😳 Any one who says otherwise doesn’t appreciate true talent in the first place,” TikTok post about The Velvet Sundown, using the song American Pie, saying that it was "the day the music died". https://www.tiktok.com/@musicnewsblitz/video/7524836529403923734?_r=1&_t=ZP-8zXxdxrOZXb.

musictmwindow. n.d. “Music through my window. Part270,” TikTok post, "finding songs so you don't have to". https://www.tiktok.com/@musictmwindow/photo/7521507338562309398?_r=1&_t=ZP-8zXvH3qQeqM.

NSF. n.d. “NSF Research Shows Americans Demand Greater Clarity and Standardization in Food Labeling.”

Oğul, Sertaç. 2024. “In tune with ethics: Responsible artificial intelligence and the music industry.” OECD AI Policy Observatory. https://oecd.ai/en/wonk/ethics-music-industry.

Pick, Geoff. n.d. “The Impact of Inaccurate Product Labeling on Customer Trust.” ClearPrint.

Polny, Jessica M. n.d. “The Evolution of Social Media Content Labeling: An Online Archive.” https://cssh.northeastern.edu/ethics/the-evolution-of-social-media-content-labeling-an-online-archive/.

Relevant_Ninja2251. n.d. “Seemingly AI-generated band The Velvet Sundown have over 400,000 monthly Spotify listeners,” Social Media Post. https://www.reddit.com/r/Music/comments/1lo1f1o/seemingly_aigenerated_band_the_velvet_sundown.

Rolling Stone Culture Council. n.d. “AI-Generated Music: A Creative Revolution or a Cultural Crisis?” Rolling Stone Culture Council. Accessed September 3, 2025. https://council.rollingstone.com/blog/the-impact-of-ai-generated-music.

Sarmiento, Isabella G. n.d. “AI-generated music is here to stay. Will streaming services like Spotify label it?” NPR.

Sharot, Tali, and Christopher A. Kelly. 2024. “Why the Internet Needs Content Labels | TIME.” Time Magazine. https://time.com/7177598/internet-content-labels-essay/.

Soundful. n.d. “A How-To Guide: Creating Music with AI Music Generators.” Soundful. https://soundful.com/en-us/how-to-guide-creating-music-with-ai-music-generators.

Straub, Jeremy. n.d. Americans' Perspectives on Online Media Warning Labels. Accessed September 8, 2025. https://pmc.ncbi.nlm.nih.gov/articles/PMC8945542/.

USDA. n.d. “Do Food Labels Make a Difference?...Sometimes.” https://www.ers.usda.gov/amber-waves/2007/november/do-food-labels-make-a-difference-sometimes#:~:text=A%20byproduct%20of%20the%20explosion,success%20of%20the dolphin-friendly%20label.

“What Is the Difference Between Ai-Assisted and Ai-Generated Content?” n.d. Clearscope.