Harmony in Dissonance: The Impact of AI Transparency on Consumer Acceptance in the Music Industry

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Abstract

The use of Generative artificial intelligence (AI) in creative industries is trending right now and has become more common in the last years, giving consumers and artists reason to worry about its ethical implementation into creative processes. Based on earlier research on ethics of AI in business, this thesis explores how the use of AI in music production influences consumer acceptance, focusing on the roles of transparency and trust. The predictions of this study were tested quantitatively in form of a normal regression and Hayes9 process models. The data used was collected from an online survey consisting of information about transparency perception towards AI and trust in AI usage in the music industry. The study reveals a significant negative impact of AI use on acceptance, highlighting persistent skepticism toward AI in creative processes. Transparency was found to be insufficient in mitigating this effect, while trust emerged as a critical factor, reducing resistance among individuals with higher trust in AI. These findings emphasize the need to build consumer trust in AI rather than relying solely on transparency to enhance consumer acceptance of AI. This study provides valuable insights for practitioners and researchers in navigating the integration of AI into creative industries, with a specific focus on marketing strategies that stress the possibilities that AI offers when integrating rather than replacing human creative process. Moreover, practitioners should not only rely on being transparent but focus on building trust in AI systems by educating audiences about capabilities and limitation of AI.

Keywords: *Gen AI, AI transparency, Trust in AI, Consumer Acceptance*

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Sumário

O uso de GenAI nas indústrias criativas tem crescido nos últimos anos, gerando preocupações sobre sua implementação ética. Esta tese investiga como a IA na produção musical afeta a aceitação do consumidor, com foco na transparência e na confiança. Para testar as hipóteses, utilizou-se regressão linear e modelos de processo de Hayes, com dados coletados via pesquisa online sobre percepções de transparência e confiança na IA na indústria musical.

Os resultados mostram um impacto negativo significativo do uso de IA na aceitação, revelando um ceticismo persistente em processos criativos. A transparência, por si só, não mitiga esse efeito, enquanto a confiança se mostrou um fator crucial, reduzindo a resistência entre aqueles que confiam mais na IA. Assim, construir confiança no uso da IA é essencial para aumentar a aceitação do consumidor.

Este estudo oferece insights relevantes para profissionais e pesquisadores sobre a integração da IA nas indústrias criativas. Estratégias de marketing devem destacar os benefícios da IA como complemento ao processo criativo humano, e não como substituição. Além disso, a construção da confiança deve ser priorizada, educando o público sobre as capacidades e limitações da IA, ao invés de depender apenas da transparência.

Palavras-chave: *Gen AI, AI transparency, Trust in AI, Consumer Acceptance*

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List of Abbreviations

AI	Artificial Intelligence
DV	Dependent Variable
GenAI	Generative AI
H1	Hypothesis 1
H2	Hypothesis 2
H3	Hypothesis 3
IV	Independent Variable

1. Introduction

1.1. Opening thought

German producer Butterbro has achieved something unique. "Verknallt in einen Talahon" is the first AI-generated song to make it into the German charts. Butterbro created the melody and vocals for his self-written lyrics using the music generator website Udio. The song became popular on youth platforms like TikTok and was temporarily removed from Spotify due to unclear copyright issues, which have since been resolved. The song's entry into the German charts at number 48, between Beyoncé and Taylor Swift, demonstrates that despite a preference for authentic human emotion in music, a catchy tune can still win over listeners (Goldmann, 2024).

1.2. Relevance of the topic and problem statement

Transparency in the literature is frequently characterized as "the right to an explanation," which refers to the capability to comprehend the processes by which an algorithm produces its results (Goodman & Flaxman, 2017; Springer & Whittaker, 2020). In the digital era, transparency entails making the rules, algorithms, and filters involved in collecting, storing, and distributing data clear and comprehensible to both individuals and organizations (Walker, 2016). Transparency indicates how visible the fundamental operating principles and internal logics of technology are to its users, and it is deemed essential for building trust in new technology (Hoff & Bashir, 2015). Hosanagar and Jair (2018) hold caution against embracing the concept of algorithmic transparency without reservations. They further argue that increased transparency could inadvertently impede companies' ability to develop algorithms. Consistently, the transparency and disclosure of AI identities could hinder the performance and efficiency of AI systems, such as bots used in customer transactions (Ishowo-Oloko et al., 2019; Luo et al., 2019). Explainable AI methods might produce explanations that are too complex for human understanding, not truly reflective of the original models, or lacking in detail necessary for clarity about the models' operations (Rudin, 2019). This situation presents a dilemma about whether intelligent machines should conceal their non-human nature to boost efficiency and how to balance the costs and benefits of transparency (Ishowo-Oloko et al., 2019; Luo et al., 2019).

Bostrom and Yudkowsky (2014) state that any criteria applicable to humans carrying out social functions should also apply to algorithms designed to substitute human judgment in these roles, highlighting several fundamental ethical principles that should guide AI technologies, including transparency. Shah et al. (2023) emphasize the significance of transparency, as examining it from the users' viewpoints offers valuable insights that can aid AI developers and practitioners in creating ethical technologies. According to them, algorithmic transparency is increasingly recognized as a best practice for addressing ethical concerns in big data and AI. Springer and Whittaker (2020) have recognized transparency as a crucial practice for holding companies accountable and averting harmful outcomes. Moreover, Greiner et al. (2020) found that the acceptance of AI can be increased through transparency and perceptible interaction. Furthermore, existing research consistently highlights that trust in AI tools is a critical factor determining human acceptance and active support for adopting these technologies (Glikson & Woolley, 2020). This trust is primarily contingent upon transparency in how AI systems make decisions and execute tasks (Ghosh et al., 2022). Consumers seem to have ambivalent attitudes towards AI technologies, stemming from the various ethical issues linked to the development and implementation of AI. Consumer trust in AI-enabled products is largely contingent on the handling of major ethical issues such as AI biases, cybersecurity, privacy, and value alignment. This trust is crucial for the broad adoption of AI-enabled products. Consequently, it is essential to explore both the ethical challenges and opportunities presented by AI-enabled value creation (Verbeek, 2011, 2014). As society grows more dependent on technology, it fosters an environment rich in data that is deeply connected with ethical concerns such as transparency, trust, and consumer protection (Walker, 2016). Many users now demand complete transparency and expect clear explanations of how these systems arrive at their decisions (Shah et al., 2023). Consequently, companies employing AI tools in consumer-facing applications face the ongoing challenge of integrating AI transparently to avoid negative reactions from consumers (Haupt, Freidank & Haas, 2024). However, demanding greater data transparency will also result in an increased amount of information for consumers to process, complicating their ability to make informed decisions and engage in protective behaviors (Walker, 2016). The opacity of the algorithms behind AI systems often makes it difficult for stakeholders to trust them, a situation referred to as the "black box paradox" (Savage, 2022).

Recent technological advancements in AI have spurred a rise in research exploring the factors that influence AI acceptance, leading to the creation or expansion of various acceptance models. However, there remains a gap in synthesizing the existing literature on user acceptance

of AI (Kelly, Kaye & Oviedo-Trespalacios, 2023). Despite the widespread belief that transparency promotes confidence in systems and organizations, this notion is not well supported by logical empirical data (Albu and Flyverbom, 2016). Particularly, trust varies among various stakeholders, depending on the timing and content of the information disclosed, as well as the clarity, accuracy, and relevance they attribute to the information (Schnackenberg and Tomlinson, 2014).

1.3. Research Objective

AI research in the music industry should consider how consumers perceive AI involvement in music creation, which can significantly influence their acceptance and potentially enhance human-machine interactions. This will provide insights into creating more efficient and well-accepted uses of AI in music production, thereby maximizing long-term value for the industry, its artists and consumers. The study aims to address the identified research gap with the research question formulated as follows:

Does the use of AI in the creation of music influence consumer acceptance of AI in the music industry, and does the transparency of AI usage mediate this influence?

2. Theoretical Background and Hypotheses

2.1. An overview of AI related ethical issues

Artificial intelligence (AI) represents more than just a technological innovation; it is a transformative power that improves societies by reducing expenses and threats, increasing dependability and consistency, and providing novel solutions to complex problems. However, only if ethics play a key role in this process, ensuring that regulations of AI harness its potential while mitigating its risks, can this power be used for the well-being of humanity. (Taddeo & Floridi, 2018). AI systems and applications have spread widely throughout various industries and sectors (Campbell et al., 2022). Technologies like AI, robots, machine learning, and Generative AI (GenAI) have already had a significant impact on how people live and work, and they will continue to change both the nature of work and the workplace (McKinsey, 2018). GenAI refers to AI systems capable of producing text, images, or other media in response to specific prompts. These systems operate using generative models like large language models, which statistically generate new data derived from the dataset they were trained on (Bi, 2023).

In 2020, the Society of Industrial and Organizational Psychology identified AI and machine learning as the top trend in the workplace, noting a surge in the number of employees utilizing these new AI technologies (SIOP, 2020). According to the state of AI study of McKinsey in early 2024, 65% of organizations are making use of GenAI on a regular basis. Maslej et al (2023) state that the implementation of AI in core business processes can significantly boost companies by increasing revenue and reducing costs. However, so far there seems to be no proof of an AI-driven boost in overall economic productivity (The Economist, 2024). According to a recent Boston Consulting Group (BCG) survey, most executives expect it will take at least two years to surpass the initial hype surrounding AI, since most companies are falling behind in embracing the full potential and benefits of GenAI (Apotheker, et al. 2024).

2.2. Transparency

<We believe that transparency is essential to responsible and trustworthy AI.= is one of the core principles for music creation with AI (Universal, 2024b). Successfully embedding ethical principles into AI-enabled products and aligning the ethical values of the product with those of the user are essential for building consumer trust and encouraging the adoption of these products (Etzioni & Etzioni, 2017). To boost user satisfaction and trust, a prevalent suggestion from both academics and developers is to enhance the transparency of how algorithms are designed. Moreover, the importance of transparency is broadly acknowledged across technical, social, and economic contexts (Shah et al., 2023). Transparency can conflict with privacy and proprietary concerns that aim to maintain exclusivity or competitive edges (Ananny & Crawford, 2018). Demanding greater transparency in data will lead to an increased volume of information for consumers to handle, complicating their ability to make informed decisions (Walker, 2016). Additionally, transparency faces cognitive challenges such as information overload and comprehension difficulties, technical hurdles like methodological complexity, and temporal issues including fast-paced advancements and development cycles (Ananny & Crawford, 2018).

When companies openly disclose their use of AI, researchers have commonly noted the occurrence of algorithm aversion, when customers express hesitation about using AI in comparison to human alternatives (Castelo et al., 2019; Dietvorst et al., 2015). Subsequently, Luo et al. (2019) found that an AI-driven digital agent, such as a chatbot, achieved conversion rates comparable to those of a skilled human sales agent, but only when the chatbot's AI identity

was concealed. When the AI nature of the chatbot was revealed, the purchase rate plummeted by more than 75% due to consumers perceiving the chatbot as less knowledgeable and empathetic than a human salesperson (Luo et al., 2019). Consistently, a meta-analysis by Graefe and Bohlken (2020) found that texts generated by AI were rated similarly to those written by humans across various studies, provided the authorship was concealed. However, when the involvement of AI was disclosed, consumer reactions varied significantly. Researchers have found that humans generally perceive AI as less trustworthy, less empathetic, and less competent (Chan-Olmsted, 2019; Luo et al., 2019). On the contrary, according to several studies, transparency in AI algorithms is also seen as a key method for earning the trust of users and the public (Felzmann et al., 2019; Lee & Li, 2021; Grimmelikhuijsen, 2023). It can not only uphold a robust reputation, develop or maintain trust, but nurture relationships between an organization and the public (Park & Yoon, 2024).

2.3. Consumer acceptance of AI

Adell et al. (2018) emphasize that the successful implementation and utilization of new technology heavily depends on human acceptance. A significant driving force behind the rapid expansion of AI technologies is the growing acceptance and adoption of AI-enabled products by consumers (Du & Xie, 2021). According to Kelly et al. (2023), acceptance is defined as the intention to use, purchase, or experiment with a product or service. Consumers exhibit conflicting emotions towards AI. Even though they appreciate the advanced capabilities of AI-enabled products, but simultaneously harbor concerns about the potential negative aspects of such potent technologies (Mick & Fournier, 1998). A key argument supporting the classification of GenAI systems as creative hinges on the observation that the art they produce is often indistinguishable from that made by humans and is widely regarded as surprising, interesting, or aesthetically pleasing (Cetinic & She, 2021). In an experiment, a mix of AICAN-generated images and contemporary artworks from the 2016 Art Basel art fair was displayed. The results revealed that 75% of the participants believed the images created by AICAN were made by human artists (Elgammal, et al. 2017). However, Hong & Curran's survey experiment in 2019 reveal distinct differences in how human-created and AI-created artworks are evaluated. Artworks created by humans were ranked noticeably higher in terms of "composition," "degree of expression," and "aesthetic value." Other previous research has also identified a negative bias in how AI-generated content is perceived compared to content created by humans (Hong, 2018; Ragot, et al. 2020).

Moreover, a survey by Salesforce showed that 74% of the questioned consumers are worried about unethical AI usage (Salesforce, 2023). Some of those ethical concerns are raised about the authenticity and originality of the art produced by AI. While AI can generate art based on learned patterns and existing styles, it lacks the intrinsic human experience and emotions that often characterize impactful artistic products (Jiang et al., 2023). Additionally, Castelo et al. (2019) demonstrated that consumers believe AI lacks the capability to successfully perform subjective tasks, resulting in diminished trust and reliance on AI. Consistent with that finding, consumer willingness to use AI has significantly declined from 2022 to 2023. According to the Salesforce survey, 73% of business buyers and 51% of consumers are still open to using AI to enhance their experiences, but these numbers have fallen from 82% and 65% respectively in 2022. Thus, companies have the chance to bridge this gap by establishing ethical guidelines and enhancing transparency around the application of the technology (Salesforce, 2023).

2.4. Trust in AI

Mayer, Davis and Schoorman (1995) define trust as "the willingness of a party to be vulnerable to the actions of another party, based on the expectation that the other will carry out a specific action important to the trustor, regardless of the ability to monitor or control that other party" (Mayer, Davis, & Schoorman, 1995, p. 712). This definition emphasizes the significance of vulnerability, and the significance of the actions involved, and it broadens the concept of trust beyond just human-to-human interactions which allows for the inclusion of trust in AI (Wang et al., 2016). Trust has become an increasingly prominent topic within the human-computer interaction (HCI) community, as demonstrated by several recently released works (Sousa, Lamas & Dias, 2014; Gulati, Sousa & Lamas, 2017, 2018; Lewis, Sycara & Walker 2018; Yagoda & Gillan 2012). This heightened focus is largely due to advancements in AI and machine learning (Kuipers 2018). Recent studies have also introduced the concept of trust as a predictor of technology acceptance, enhancing our understanding of how it influences user interactions with technology (Ghazizadeh, Lee, & Boyle, 2012; Hoff & Bashir, 2015; Lee & See, 2004; Pavlou, 2003). Trust is known to reduce risk, uncertainty, and anxiety when interacting with technologies (Söllner et al. 2012) and to foster positive and meaningful technological experiences (McKnight et al. 2011). According to Benbasat and Wang (2005) it is essential for encouraging users to gradually and consistently engage with the system.

Despite the increasing adoption of AI by companies, consumer trust in AI remains low. This is shown in an experiment carried out by Ragot et al. in 2020 in which they had participants assess the differences between paintings made by humans and those created by AI, focusing on the factors liking, perceived beauty, novelty, and meaning. The results revealed that The paintings assigned to AI were regularly evaluated lower than those thought to be created by humans. This innovative approach in their methodology and sampling underscored a clear perceptual bias against AI, demonstrating a preference for human-created works (Ragot et al., 2020).

2.5. Creativity and GenAI

Creativity is essential for a company's innovation and competitiveness (Baucus et al. 2008). In management studies creative industries are often described as sectors that are designed to create and profit from artistic and cultural expression (Jones, Lorenzon & Sapsed, 2015; Jones & Maoret, 2018; Godart, Seong & Phillips, 2020). Traditionally a human-dominated industry, the emergence of GenAI is transforming the landscape of the creative industry (De Cremer, Bianzino & Falk 2023). Jiang et al. (2023) characterize art and creativity as an endeavor uniquely tied to human culture and experience, distinguishing it as a distinctly human activity. Today it is becoming more and more common to use GenAI technologies like ChatGPT and Midjourney that are poised to revolutionize the realm of creative occupations. To adapt to the transformation, challenges presented by this change must be identified and understood as a preparation for a future where creativity involves both human and machine collaboration (De Cremer, Bianzino & Falk 2023). While AI has the potential to be a new medium for artistic expression, its current use raises significant ethical, economic, and legal concerns that need to be addressed to protect the rights and livelihoods of human artists (Jiang et al., 2023). Islam and Greenwood (2024) found that programs that use GenAI rely on a jointly produced labour and inputs that are essentially invisible or untraceable and refer to them as a "hypercommons". The term "hypercommons" refers to the idea that digital technologies are built on and benefit from a wide range of inputs and interactions that occur on digital platforms.

GenAI automates various authorial tasks, ranging from basic spelling checks to complex producing and editing text. Although the veracity and precision of content produced by GenAI may not match expert levels, it often appears convincing enough to be mistaken for professional work with minor revisions (Islam & Greenwood, 2024).

In 2020 Nike collaborated with the Parisian artist group Obvious to create new designs for the Air Max sneaker by using a GenAI model trained with images of earlier Air Max models. The artists refined the suggested designs to align with Nike's brand and current fashion trends, resulting in a style that balanced innovation with Nike's traditional aesthetic. The final design featured familiar Air Max elements combined with new colors and patterns, creating a fresh look in a limited-edition sneaker which sold out within ten days (De Freitas & Ofek, 2024). This example implies that customers are willing to buy products that where designed or generated with AI.

However, Donahue (2023) stated that musicians' voices are being "deepfaked" and used in songs and productions that they never truly created or performed. In the music industry, a deep fake involves using sophisticated AI technology to produce audio content that is realistic and sometimes misleading. This includes synthesizing voices, replicating instruments, and mimicking songwriting styles (Henkin, 2023). Moreover, the painter and illustrator Molly Crabapple leads a group of artists challenging the use of their work by companies that feed their creations into AI programs like Stable Diffusion or DALL-E 2 to produce similar artworks. They argue that these AI generators, trained on vast datasets of copyrighted images without creators' consent or compensation, represent a significant art theft, facilitated by well-funded, reputable firms (Klein, 2023). However, some artists point out that the emotional bond between artists and their audiences is something AI cannot artificially create (Scheiber & Koblin, 2023).

It is certain that required skillsets in different industries are going to change due to the use of AI. Especially technological and creative related skills seem to be required more and more (McKinsey, 2018). As AI replicates styles and produces art based on existing works, it challenges the concepts of originality and personal expression, key to the identity of human-made art (Samuelson, 2023). Researchers, technologists, and artists have become increasingly interested in utilizing AI's creative potential in recent years (Goodfellow, et al., 2014). Since AI tools are becoming more integral to art creation, artists may need to adapt to digital and AI-driven tools into their creative process to remain competitive, potentially altering their traditional working styles (Samuelson, 2023). Adding on to that, Cetinic and She (2022) suggested that AI will continue to play a crucial role in both understanding and creating art. They state that as AI technologies further evolve, they will increasingly influence how art is created, understood, and valued (Cetinic & She, 2022).

2.6. Generative AI in the music industry

The music industry is characterized by an interconnected network that encompasses the production, distribution, marketing, and consumption of music across digital and physical platforms, alongside the promotion of live performances (Tschmuck, 2021).

One very recent development of the use of AI in the music industry is the partnership between SoundLabs, an artist-founded AI technology company and Universal Music Group (UMG). They launched MicDrop, an AI vocal plugin that allows real-time voice transformations. Developed by SoundLabs, co-founded by BT and other experts, MicDrop supports innovative vocal capabilities like language transposition and singing in different voices. The collaboration focuses on ethical AI use, ensuring artists control their creative outputs. SoundLabs is committed to enhancing musical creativity with AI, while UMG supports using technology to expand artistic opportunities (Universal Music Group, 2024a). Other AI tools, such as AIVA and Songwriter from Amper Music are being used in order to assist musicians with creating original lyrics, chord progressions, and melodies. AI-powered arrangement tools, such as Presonus' Notion and BandLab's Band-in-a-Box, can assist musicians in writing and perfecting the structure of their songs (Henkin, 2023). The rapid integration of GenAI took place especially in music, impacting streaming, songwriting, and production. AI tools analyze user preferences on platforms like Spotify to offer personalized music recommendations and adjust streaming quality (Hunter-Tilney, 2023). This not only broadens listeners' musical experiences but also offers artists a potential tool to connect with new and engaged audiences (Henkin, 2023). In songwriting, apps like Boomy and MusicLM generate music from simple prompts. Following allegations that bots were being used to artificially boost streaming numbers and revenues, Spotify removed thousands of such tracks created by Boomy from its catalog. AI's role in music production is growing, with technologies like audio source separation making music creation more accessible and interactive. However, the industry, including major labels, is cautious about AI's implications for copyright and authenticity. However, Jessica Powell, chief executive of San Francisco-based start-up Audioshake states, that concerns about AI dominating the music industry are exaggerated. She believes that human creativity will remain essential, even as technology increasingly influences the nature of the work (Hunter-Tilney, 2023). Consistently, Askin & Mauskapf (2017) found that musical artists often employ a strategy of optimal distinctiveness by balancing innovation with familiarity to captivate their audiences and secure a competitive edge. Moreover, scientific articles now frequently discuss

the application of artificial intelligence in general and Deep Learning-based technologies in particular for musical composition (Civit et al. 2022).

AI music generators analyze existing music using machine learning algorithms, then produce new compositions based on their findings. In 2021, a collaboration between computer scientists and musicians employed an artificial neural network to develop realizations of the third and fourth movements of Beethoven's Tenth Symphony for which composer Ludwig van Beethoven, who passed away in 1827, had left behind numerous sketches (Brandt, 2023). This implies that musicians can use AI-generated music to build complete tracks. For composers and artists, this technology may seem like a time-saver, but it has also brought up some moral questions. For example, some claim that music produced by AI is less authentic and innovative than music created by human musicians. Some are concerned that AI-generated music may eventually replace human musicians and composers, forcing them out of their jobs (Rolling Stone Culture Council, 2024). Henkin (2023) argues that a balanced strategy that uses technology while simultaneously addressing ethical issues and obstacles is what offers the most value to everyone. The music industry is positioned to quickly fuse AI with human creativity, paving the way for a time when technology and skill will combine to create music, and innovation will offer the sector numerous chances to expand and change. Moreover, he states that there is a ton of commercial potential, ranging from manufacturing and composition revolutions to distribution optimization. AI is also improving and personalizing the fan experience and making music creation and production simpler, easier, and more affordable (Henkin, 2023).

Table 1. *Types of AI technologies in the music industry*

Types of Technology	Use and Purpose	Organizations
MicDrop	AI vocal plugin for real-time voice transformations Focus on ethical use of AI	UMG, SoundLabs
AIVA	Creation of lyrics, chord progressions, melodies	Musicians By Amper Music
Songwriter	Creation of lyrics, chord progressions, melodies	Musicians By Amper Music
Notion	Music composition	Musicians

	Writing and perfecting structure of songs	By Presonus
Band-in-a-Box	Writing and perfecting structure of songs	Musicians By BandLab
Boomy	Songwriting Generating music from simple prompts	Independent music creators Spotify, Apple Music, YouTube Music
MusicLM	Songwriting Generating music from simple prompts	

3. Data and Methods

3.1. Hypotheses

Based on the already existing theory on AI transparency and its acceptance by the consumer and the potential use of AI in the music industry, the following Hypotheses were posed to answer the research question of this study:

H1: The use of AI in the song production has a negative impact on the acceptance of AI by the consumer.

H2: Transparent use of AI mediates the relationship between the use of AI and customer acceptance such that the more transparent the artist is with the use of AI in his work, the higher the level of consumer acceptance.

H3: The individuals trust in AI moderates the indirect effect between transparency and acceptance such that the mediated relationship is stronger when the trust is stronger.

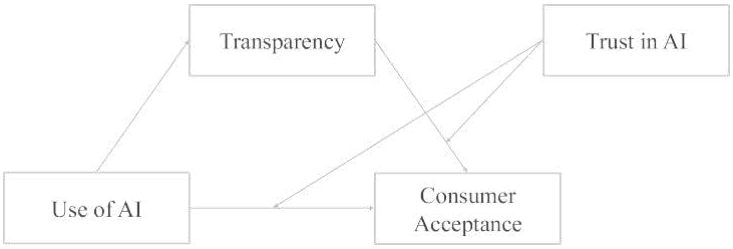

Figure 1. Conceptual Model

3.2. Research Design

The aim of this study is to investigate the effect of the use of AI in the creation of music on the consumer acceptance of AI in the music industry. The extent to which the relationship is mediated by the transparent use of AI and moderated by the individuals overall trust in AI should be determined.

A quantitative approach was used to answer the research question and to build upon earlier research regarding the importance of transparency and consumer trust in AI in influencing its acceptance (Luo et al. 2019, Greiner et al. 2020) and to make sure to get precise findings through an objective measurement of variables. In order to test the causality of the hypothesized relationships a between-subjects experimental design approach was chosen (Hulland et al., 2018) in the form of a questionnaire in an online study with Qualtrics to investigate consumer acceptance of AI-created music (Appendix 1). This structured approach allows to compare different groups with different conditions and provides strong statistical evidence to support conclusions and since the research question of this thesis is focused on investigating the effect of AI use on consumer acceptance, a quantitative approach aligns well. The questionnaire was distributed online mainly among people with an intensified interest towards music and the music industry. A <between-subjects= comparative design was chosen in which each participant is exposed to just one treatment condition. Participants were randomly assigned to one of the following groups and provided with a brief scenario: (1) AI-created music, and (2) human-created music. As long as participants are randomly assigned to groups, causal relationships can be determined by comparing the behaviors of individuals between the treatment conditions in the two different groups (Charness, Gneezy & Kuhn, 2012).

In order to obtain a more comprehensive explanation of the causal effect investigated, transparency is treated as a mediating variable, hypothesized to influence how AI-created music impacts consumer acceptance. The role of transparency is measured only within the AI group, enabling an assessment of whether knowledge of AI use makes participants more accepting of AI in the music industry. Moderation analysis, in contrast, assesses whether the strength or direction of the relationship between an independent and dependent variable varies depending on the level of a third variable (Hayes, 2013). The PROCESS models by Hayes (2013) offer robust techniques for simultaneously testing mediation and moderation effects in

experimental data. Here, trust in AI is measured across both groups to determine if it strengthens or weakens consumer acceptance of AI-created music. This approach enables a deeper understanding of individual differences in responses to AI in music creation.

3.3. Participants

Between November 8th and November 22nd, a total of 209 surveys were completed. However, 49 participants had to be excluded from the survey because they did not answer the attention question correctly or there was some missing data. This led to a total valid sample of 160 participants (43.13% male / 56.88% female) with an age range from 18 to 62 years (M = 33 / SD = 13.11). To summarize, 84 participants were randomly assigned to the non-AI group and 76 to the AI group (52.5% non-AI / 47.5% AI). 143 of the participants are using Spotify, 48 YouTube Music, 26 Apple Music, 34 SoundCloud and 102 use more than one platform to stream their music. 113 of the participants listen to Pop, 81 to HipHop, 74 to Electronic Music, 62 to Rock, 25 to Jazz, and 132 listen to more than just one genre. On average the participants use two platforms to stream their music and listen to three different genres.

3.4. *Procedure*

The data was collected using a non-probability sampling technique (Stevens, et al., 2005). The voluntary participants were found via social networks such as Facebook groups, LinkedIn, Instagram. After consenting to participate, all study participants were asked to indicate their trust in AI. Those questions were included before participants were randomly assigned into two groups to avoid any biases and correlation.

The next step was a random assignment of each participant of the following groups including a brief scenario description. After reading the scenario description all participants, regardless of their group, responded to the same questions to measure consumer acceptance. The study measured consumer acceptance as the primary dependent variable, with transparency and trust in AI as additional predictors. Questions about their transparency perception were posed to measure transparency as a mediating variable. An attention check question was designed to make sure participants were paying attention to the questions and for data cleaning. Participants that failed the attention task were removed from the final data pool. Finally, demographic data was collected, and participants were asked to give information about their familiarity with AI,

the frequency of their music consumption, their music genre preferences and platforms they typically use for listening to music.

3.5. Variables

3.5.1. Dependent Variable

AI Acceptance. This study defined the acceptance of AI in the music creation process as the dependent variable. Participants in each group responded to six identical questions assessing enjoyment, authenticity, willingness to purchase, and general acceptance of the creation process on a seven-point Likert-scale alike (1=Strongly Disagree; 7=Strongly Agree). One example item states *<I would be likely to purchase or stream this song=*. The mean of those questions constitutes the DV and allows for comparability across groups while enabling the measurement of transparency's mediation effect and the moderation effect of overall trust in AI.

3.5.2. Independent Variable

Use of AI. The independent variable in this study was measured as a binary variable in the previously described experiment. It represents if AI has been used and played an important role in the composition and production of a new song vs. if the song was entirely created by a human-artist. Participants were randomly and evenly assigned into two different groups with two different scenarios. Group 1 (AI group) was given the following scenario: "*Imagine a popular new song has been released. This song was created using advanced AI technology, with AI tools playing a significant role in the composition and production of the music."* Group 2 (Non-AI group) was given another scenario: *"Imagine a popular new song has been released. This song was created entirely by human musicians and producers without any AI involvement in the composition or production."*

3.5.3. Mediator

Transparency. The mediator transparency consisted of five items including the importance, impact and level of transparency, using a seven-point Likert-scale alike (1=Strongly Disagree; 7=Strongly Agree). One example item reads as *<Artists and producers should always disclose when AI has been involved in creating a piece of music.=*

3.5.4. Moderator

Trust in AI. The moderator variable was measured on a seven-point Likert-scale alike (1=Strongly Disagree; 7=Strongly Agree) and included five items. One example item reads *<I trust AI can competently create music that is enjoyable and of high quality.=*.

3.5.5. Control Variables

Demographics. Age, gender and educational level in the form of which degree the participant holds were also included to cover demographic data and make use of them as covariates.

Familiarity. To get a better understanding for the participants overall understanding of AI-created music, they were presented the item *<How familiar are you with the concept of AI-created music, where artificial intelligence assists in composing or producing songs?=,* again using a seven-point Likert-scale alike (1=not familiar at all; 7=extremely familiar).

Regularity. Since people have different levels of frequencies when listening to music, it is important to control for that timespan. The question on how often they listen to music was included in the questionnaire with answer opportunities *<Daily, Weekly, Monthly, Rarely, Never=*.

Music Genre Preferences. It seems particularly interesting to see if there are any differences in the different genres which is why participants had to give their music genre preference. They were also given the opportunity to specify any other genres in an extra text box.

Platforms. Moreover, participants were asked which platforms they use to listen to music and were given the possibility to choose more than one answer and a textbox to give any additional information. Platform examples included *Spotify, Soundcloud, YouTube, Amazon Music, Apple Music* and a few more.

3.6. Statistical Method and Analysis

For statistical computing and analysis, R-Studio was used. Descriptive statistics were presented to gain an overall understanding of the respondents' demographics and distributions. Afterwards, the variables acceptance, trust and transparency were created by taking the mean of the Likert-scale alike responses (Appendix 2). In addition, Cronbach's alpha was conducted

for reliability testing (Appendix 3). To test the effect of the *use of AI* on *consumer acceptance* (H1) a normal regression was used (Appendix 4). This method was chosen because the DV is continuous and aligns with the assumptions of normal regression, including linearity, homoskedasticity, and normally distributed residuals which were tested and confirmed. Furthermore, given the sample size of 160 participants, normal regression was deemed appropriate for ensuring valid hypothesis testing and accurate estimation of confidence intervals. For the evaluation of the results for H2 and H3, model 4 (Figure 2) and model 15 (Figure 3) of the process macro developed by Hayes (2013) were applied (Appendix 5, 6). Paths a and b represent the indirect effect which describes the assumption of H2. They display the relationship that flows from the IV *use of AI* to the mediator *transparency* and to the DV *consumer acceptance*. Path c´ explains the direct effect of *use of AI* on *consumer acceptance* with the presence of the mediator *transparency*.

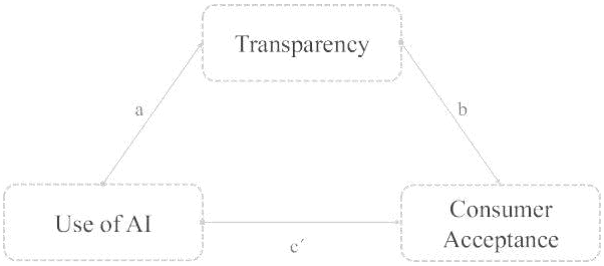

Figure 2. The Process Macro – Model 4

For H3 the moderator *trust in AI* was added, by choosing model 15 of the process macro for the analysis. Model 15 tries to determine if the moderator *trust in AI* is changing the strength of the mediation effect of *transparency* and the direct effect of *use of AI* on the *consumer acceptance of AI*, which has already been analyzed in model 4.

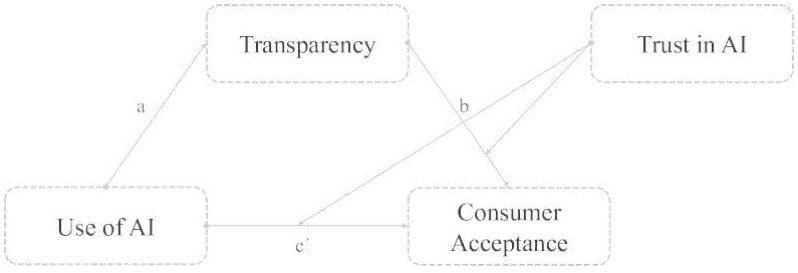

Figure 3. The Process Macro – Model 15

4. Results

4.1. Data Analysis

After cleaning the dataset in Excel and removing participants with missing data, in order to conduct an exact and comprehensively analysis of the data from the online survey, R-Studio has been used. To gain an overall understanding of the dataset and the respondents' demographics, descriptive statistics have been applied. Afterwards, to evaluate the reliability of the different scales, Cronbach's alpha was applied. Multiple regression analysis and the process models of Hayes (2013) were conducted to provide precise models.

4.2. Scale Reliability

Reliability testing of the variables *transparency*, *trust in AI*, and *consumer acceptance* was conducted by applying Cronbach's alpha. Transparency yielded a raw alpha of 0.78 which is higher than 0.70 and is therefore an indicator for good internal consistency. The alphas for the scenario groups AI and non-AI yielded into values of 0.72 and 0.79 which are a sign of acceptable reliable scales. The scale for trust in AI yielded a Cronbach's alpha of 0.42. This low alpha implies low reliability, however, can still be accepted in this case. The trust items can be mainly clustered into performance-based trust (*trust 1, trust 2, trust 3*) and ethical trust (*trust 4 and trust 5*), reflecting the multidimensional nature of the construct, which contributes to the lower Cronbach's alpha as it measures internal consistency within, rather than across dimensions. Moreover, scales with fewer items seem to have lower reliability due to limited coverage of the construct.

4.3. Hypothesis Testing

To investigate the effects of the IVs on the DV *consumer acceptance* multiple regression analysis was conducted. H1 tested if the *use of AI* in song production has a negative impact on the *acceptance* of AI by the consumer. The results of the regression analysis represented in Table 2 show statistical evidence for the support of the hypothesis that the *use of AI* negatively impacts *consumer acceptance* of AI in music production. The *use of AI* demonstrates a highly significant negative effect ($p < 0.001$). The *use of AI* in song production reduces the *consumer acceptance* of AI by an average of 2.28 points compared to non-AI song production, holding all other variables constant. The R-squared of 0.536 indicates that 53.6% of the variance in the DV is explained by the independent variables in the model. After accounting for the number

of predictors, the model still explains a substantial 51.8% of the variance (adjusted R-squared=0.518). The control variables *familiarity, regularity, gender, age* and *degree* do not significantly influence AI acceptance.

Table 2. *Model H1*

	Dependent variable
	Consumer Acceptance
Use of AI	-2.283***
	(0.181)
Familiarity	-0.037
	(0.054)
Regularity	-0.040
	(0.209)
Gender	-0.255
	(0.185)
Age	-0.008
	(0.007)
Degree	-0.012
	(0.085)
Constant	6.533***
	(1.153)
Observa珞椀ons	160
R^2	0.536
Adjusted R^2	0.518
Residual Std. Error	1.113 (df = 153)
F Sta珞椀s珞椀c	29.471*** (df = 6; 153)
Note:	*p<0.1; **p<0.05; ***p<0.01

H2 is supposed to test if the transparent use of AI mediates the relationship between the *use of AI* and *consumer acceptance* such that the more transparent the artist is with the *use of AI* in their work, the higher the level of *consumer acceptance*. For the outcome variable consumer acceptance, the model explains 53.63% (R-squared=0.5363) of the variance, suggesting a strong direct effect model. As shown in Table 3, the IV *use of AI* has a strong negative effect on the DV *consumer acceptance* with a ß= –2.2891 and a p<0.01, again suggesting that the *use*

of AI in the music industry impacts the *consumer acceptance* of AI negatively. However, none of the covariates (*familiarity, regularity, gender, age, degree*) have significant effects on either *transparency* or *consumer acceptance*.

Table 3. *Results for the outcome variable consumer acceptance in Model 4.*

	Coefficient	SE	t	p	LLCCI	ULCI
Constant	6.4281***	1.2447	E.1642	0.0000	3.9689	8.8874
Use of AI	−2.2891***	0.1837	−12.4641	0.0000	−2.6E19	−1.9262
Transparency	0.0206	0.0906	0.2270	0.8207	−0.1E84	0.199E
Familiarity	−0.0386	0.0EE0	−0.7013	0.4842	−0.1472	0.0701
Regularity	−0.0389	0.2100	−0.18EE	0.8E31	−0.4E38	0.37E9
Gender	−0.2604	0.1873	−1.3902	0.166E	−0.630E	0.1097
Age	−0.0078	0.0071	−1.1113	0.2682	−0.0218	0.0061
Degree	−0.010E	0.08E6	−0.1230	0.9023	−0.1797	0.1E87

***p < 0.01
Note: LL=lower limit. UL=upper limit. CI=confidence interval.

The results represented in Table 4 show that the indirect effect of *use of AI* on *consumer acceptance* via the mediator *transparency* is not significant, as the confidence interval includes zero (Effect size=0.0061, BootCI= [−0.0566,0.0829]). When partially standardized the indirect effect remains extremely small (Effect size=0.0038), but still does not show any significance (BootCI= –0.0356,0.0527). While the hypothesis suggested that greater transparency would improve consumer acceptance, the results indicate that transparency is neither significantly affected by the use of AI (p=0.0697) (Appendix 7) nor significantly impacts consumer acceptance (p=0.8207) (Table 3). Those results indicate that transparency does not significantly mediate the relationship between the use of AI and consumer acceptance which implies that H2 does not find any support by the data. The findings suggest that transparency alone is insufficient to mitigate the negative impact of AI use on consumer acceptance.

Table 4. *Results for the indirect effect of the use of AI on consumer acceptance through transparency.*

Transparency	Effect size	Boot SE	LL 9E% CI	UL 9E% CI
Indirect effect	0.0061	0.0329	−0.0E66	0.0829

Partially standardized indirect effect	0.0038	0.0207	−0.03E6	0.0E27

Note: Bootstrap samples = 10,000. LL=lower limit. UL=upper limit. CI=confidence interval.

H3 assumes that the individual's trust in AI moderates the indirect effect between transparency and acceptance, such that the mediated relationship is stronger when trust is stronger. For testing the moderated mediation model 15 by Hayes (2013) has been used. The moderated model tests direct and indirect effects of *use of AI* on *consumer acceptance* and whether *trust* moderates the direct effect of *use of AI* on *consumer acceptance* and the indirect effect of *use of AI* through *transparency*. For the outcome variable *consumer acceptance* 59.21% (R-squared=0.5921) of the variance is explained, which is substantial. As presented in table 5, the interaction between *use of AI* and *trust in AI* significantly predicts *consumer acceptance* with ß=0.8543 and p=0.002. This suggests that trust moderates the direct effect of the *use of AI* on *consumer acceptance*, making the effect less negative when the individual's trust in AI is higher. However, the interaction between *transparency* and *trust* does not significantly predict *consumer acceptance* (ß= –0.019 | p=0.8343). This indicates that trust does not moderate the relationship between *transparency* and *consumer acceptance*.

Table 5. *Results for the outcome variable consumer acceptance in Model 15.*

	Coefficient	SE	t	p	LLCCI	ULCI
Constant	E.29E2	2.4130	2.1944	0.0298	0.E271	10.0633
Use of AI	−E.9001***	0.9E69	−6.16E6	0.0000	−7.7910	−4.0091
Transparency	0.0331	0.4013	0.0824	0.934E	−0.7600	0.8261
Trust	−0.0442	0.4620	−0.09E6	0.9240	−0.9E70	0.8687
Use of AI x Trust in AI	0.8E43***	0.2220	3.8483	0.0002	0.41E6	1.2929
Transparency x Trust	−0.0190	0.0909	−0.2096	0.8343	−0.1986	0.160E
Familiarity	−0.0329	0.0E33	−0.6171	0.E381	−0.1381	0.0724
Regularity	0.2611	0.2102	1.2420	0.2162	−0.1E43	0.676E
Gender	−0.2717	0.1780	−1.E260	0.1291	−0.623E	0.0801
Age	−0.0064	0.0068	−0.9487	0.3443	−0.0198	0.0070
Degree	0.0283	0.0821	0.3443	0.7311	−0.1340	0.190E

***p < 0.01

Note: LL=lower limit. UL=upper limit. CI=confidence interval.

The conditional effects represented in Table 6 show the direct effects of *use of AI* on *consumer acceptance* examined at different levels of *trust*. The table shows that the direct negative effect becomes less severe as trust increases, demonstrating the moderating role of trust. At low levels of trust is highly significant and negative with an effect size of −2.8248 and p<0.001. At medium levels of trust the effect is highly significant and negative, but less negative than at low trust with an effect size of −2.1414 and p<0.001. Lastly, at high levels of trust, the effect is still highly significant and negative, but even further reduced with an effect size of −1.4579 and p<0.001.

Table 6*. Results for the conditional direct effect of the use of AI on consumer acceptance through appreciation across trust levels.*

Trust	Effect size	Boot SE	LL 9E % CI	UL 9E% CI
Low trust	−2.8248	0.2276	−3.274E	−2.37E0
Middle trust	−2.1414	0.1824	−2.E018	−1.7809
High trust	−1.4E79	0.2790	−2.0092	−0.9067

Note: Bootstrap samples = 10,000. LL=lower limit. UL=upper limit. CI=confidence interval.

Additionally, the conditional indirect effect represented in Table 7 of the *use of AI* on *consumer acceptance* via *transparency* is examined at different levels of trust but shows no sign of significance at any level of trust as the confidence intervals for all levels include zero. This indicates that trust does not significantly moderate the indirect effect. Moreover, the index of moderated mediation is at –0.0056 with a BootCI= [−0.075,0.0656]. Since the CI includes the zero, again the index is not significant which shows there is no evidence that trust moderates the mediated relationship between *use of AI* and *consumer acceptance* via *transparency*. Those findings lead to the conclusion that H3 does not find any support.

Table 7. *Results for the conditional indirect effect of the use of AI on consumer acceptance through transparency across trust levels.*

Trust	Effect size	Boot SE	LL 9E % CI	UL 9E% CI
Low trust	−0.010E	0.0392	−0.08EE	0.0821
Middle trust	−0.01E0	0.0317	−0.0740	0.0E96

High trust	−0.019E	0.0432	−0.0960	0.0830
Index of moderated mediation	−0.00E6	0.0331	−0.07E0	0.06E6

Note: Bootstrap sanples = 10,000. LL=lower linit. UL=upper linit. Cl=confidence interval.

In general, Hayes' PROCESS macro uses bootstrapping to estimate indirect effects, making it robust to violations of normality. Therefore, skewness only must be tested if there is a suspect of extreme non-normality in variables like *trust*, *transparency*, or *consumer acceptance*, which could affect interpretability. However, to make sure that the results were not skewed a skewness test was run on those variables. All three of them were slightly negatively skewed which shows the distribution has a longer tail on the left side and the bulk of the values are concentrated on the right side of the distribution. Those are signs of more participants reporting higher levels of *trust*, *transparency* and *consumer acceptance* and only fewer reporting lower levels. However, the skewness levels are $< |1|$ which does not require a transformation of the variables to normalize them.

5. Discussion

This thesis aimed to explore the role of transparency in consumer acceptance as an ethical dimension of AI in business and if transparency mediates the relationship between the use of AI and consumer acceptance.

Aligned with what Ragot et al. (2020) found in their article about AI-generated vs. human-generated artworks, this research found that there are some negative perceptions towards AI-created content in comparison to human-created work. Regression analysis revealed that the use of AI in song production has a significant negative impact on consumer acceptance reduces acceptance by 2.28 points compared to human-created songs, as hypothesized. Control variables like regulartiy of listening to music, familiarity with AI, gender, and age did not significantly affect the outcome. Contrary to earlier research by Luo et al. (2019) and Greiner et al. (2020) the analysis showed that transparency does not significantly mediate the relationship between the use of AI and customer acceptance. The indirect effect via transparency was not statistically significant and transparency itself had no significant impact on consumer acceptance which shows that AI transparency alone is insufficient to mitigate the negative perception of AI use in music creation.

Trust in AI was expected to moderate the mediated relationship between transparency and acceptance. The results showed that trust significantly moderates the direct relationship between the use of AI and consumer acceptance, making the negative effect of the use of AI less severe as trust increases. This suggests that individuals with higher trust in AI have fewer negative attitudes towards the use of AI in music creation which is aligned with the findings of the research by Söllner et al. (2012). However, trust was not found to moderate the indirect effect of transparency on consumer acceptance, as the confidence intervals include zero for all trust levels. Moreover, the interaction between transparency and trust is not significant, suggesting that trust does not hold any influence on how transparency impacts consumer acceptance. Those results show that trust plays a pivotal role in alleviating the negative impact of AI but does not enhance the mediating role of transparency as hypothesized.

These findings emphasize the challenges in overcoming consumer skepticism about AI in creative fields and highlight trust as a critical factor in improving consumer acceptance. The lack of significant mediation by transparency suggests that other factors might influence consumer perceptions more strongly and significantly.

5.1. Theoretical Contribution

This research contributes to the literature on ethics of AI and transparency in AI usage by identifying the negative impact of the use of AI on consumer acceptance. Adding on to that this research suggests that transparency alone is not sufficient enough to mitigate the negative consumer perceptions of AI use and that the overall trust in AI plays a crucial role in moderating the negative impact of the relationship between AI use and consumer acceptance.

This study identifies a persistent skepticism among consumers toward AI-created content in music production, confirming earlier research on identified negative biases toward AI-generated content (Hong, 2018; Hong & Curran, 2019; Ragot et al., 2020). By doing so, it highlights the ethical challenge of integrating AI into creative industries where consumers expect authenticity and human involvement. These findings contribute to the broader discourse on AI ethics by emphasizing the need for ethical implementation strategies that address emotional and experiential gaps in AI-generated content (Jiang et al., 2023). This study enriches the theoretical understanding of how ethical concerns, such as the lack of human

experience in AI-generated content, negatively impact consumer perceptions and acceptance. Contrary to much of the existing literature that emphasizes transparency as a key driver of consumer trust and acceptance (Shah et al., 2023; Felzmann et al., 2019; Lee & Li, 2021), this research finds that transparency alone is insufficient to mitigate negative consumer perceptions of AI use. This study expands the theoretical framing of transparency in AI ethics (Shah et al., 2023; Walker, 2016; Luo et al., 2019; Felzmann et al., 2019; Lee & Li, 2021; Grimmelikhuijsen, 2023) by demonstrating that transparency must be complemented by other factors, such as trust in AI, to have a meaningful impact on consumer acceptance. By situating transparency within the ethical framework of AI usage, this research offers a nuanced perspective that transparency, while necessary for ethical alignment, may not directly translate into consumer acceptance unless it addresses deeper concerns about trust and human-AI collaboration. This study underscores the critical role of trust in moderating the relationship between AI use and consumer acceptance, building on prior research that positions trust as a key predictor of technology acceptance (Ghazizadeh, Lee, & Boyle, 2012; Hoff & Bashir, 2015; Lee & See, 2004; Pavlou, 2003). Specifically, it demonstrates that higher levels of trust in AI reduce the negative impact of AI use on consumer acceptance, a finding that aligns with and extends the work of Ragot et al. (2020), who noted that trust in AI still remains relatively low. By integrating trust into the context of creative industries, this research provides a theoretical contribution that bridges trust and ethics in AI acceptance models, suggesting that enhancing consumer trust is essential for overcoming resistance to AI in contexts where creativity and human input are highly valued. In the following chapter important practical and managerial implications on how to increase consumers' trust levels and how to fight against negative perceptions towards AI are being discussed.

5.2. Practical & Managerial Implications

The strong negative effect of AI use on acceptance highlights a potential barrier to widespread consumer adoption of AI-generated content in music. These findings offer actionable practical guidance for managers and companies by suggesting interventions in the form of marketing strategies which may be needed to improve consumer perceptions of AI in the music industry. It could be helpful to focus on improving consumer perceptions of AI in music production, by addressing possible consumer concerns regarding the ethical implementation of AI. Another beneficial action would be to emphasize the human involvement in the creation process instead of marketing the product as fully AI-generated focusing on wordings like <enhanced by AI=

rather than <created by AI=. Highlighting collaborative efforts between artists and AI tools could improve consumer acceptance like the earlier mentioned Nike artist-AI collaboration which was a great success (De Freitas & Ofek, 2024).

Since transparency does not significantly affect consumer acceptance, an implication would be that transparency should not be the primary focus for driving acceptance, but still can play a role in reinforcing trust and ensures an alignment with ethical standards. Practically spoken, transparency should be used to show audiences how AI improves efficiency and enhances the outcome without replacing human artists and acting more like a supplement and not a substitute. A balanced approach which is providing enough clarity to foster understanding while avoiding information overload is likely to be more effective in addressing consumer skepticism. Storytelling techniques or visual examples to illustrate how AI amplifies creativity without diminishing human input. Managers should be careful to not overwhelm and overload consumers with information, which could make it more difficult for them to understand how AI works, as stated by Ananny & Crawford (2018). Still, offering the possibility to deep dive into the technical processes of the used AI tools could enhance the consumers trust in AI (Felzmann et al., 2019; Lee & Li, 2021). Given that trust moderates the direct effect of AI use on consumer acceptance, managerial efforts should focus on building trust in AI systems on the consumer side to reduce skepticism and to mitigate negative perceptions towards AI created music. Some actionable steps to make that possible would be to educate audiences and listeners about capabilities and limitations of AI in music creation through campaigns or artist interviews. This includes partnerships with well-known and trusted artists when introducing AI-generated content and being exceptionally transparent about ethical standards to address consumers concerns about authenticity and fairness. Some steps would be to develop and publish ethical guidelines for AI in the music industry and to engage stakeholders, including artists and audiences in the process to make sure AI is used in an appropriate and ethical manner. To make sure that the negative perception of AI-created music is shifting into a sort of acceptance and normalization, managers should focus on AI becoming a natural and long-term part of creative industries such as the music industry. Beneficial, among other things, would be the integration of AI-generated music into major festivals or events and to highlight such success stories to make sure audiences are aware and more open-minded.

5.3. Limitations and Future Research

By offering these insights, this research contributes to a deeper understanding of the consequences of the use of AI in the music industry and opens avenues for further exploration possibilities which are described in this paragraph.

Since the study is based on a cross-sectional design it measures the relationships at one point in time and does not capture possible changes in perceptions over time. Since AI is a relatively new and recent field of study, changes in perceptions may occur quickly over a short period of time. To observe how consumers perceptions evolve over time as AI becomes more integrated into creative industries, one possibility for future research could be to conduct a longitudal study. The trust scale shows low reliability (Cronbach's alpha = 0.42) which may be a weakening factor for the findings related to the moderation effect. A more robust measure of trust in AI might yield into clearer and more significant insights and results. Therefore, suggesting a redesign of the trust scale to improve reliability and validity of the results. One approach would be to incorporate different aspects like the competence, benevolence and integrity of AI systems and tools used in the music industry. It was found that transparency alone may not be sufficient to improve consumer acceptance. Future research could explore other mediators or moderators, such as the emotional connection, perceived authenticity or perceived quality. One possible way to look at this could be to reconsider the transparency role in the model and to investigate whether those other variables might better explain or mediate the relationship between AI use and consumer acceptance. To explore consumer perceptions, conducting qualitative or mixed-methods research to understand why transparency does not seem to influence consumer acceptance could be one possible solution. A potential bias that could occur is that participants may already have preconceived notions about AI in creative fields which partly could influence their responses. Moreover, since the study was using an experimental design approach, participants were told in the beginning whether the songs are AI-generated. In a real-life scenario, consumers may not know or notice that AI has been used in the creation process of that particular song. For future studies, a field study in a real-world setting could be conducted. One possible approach would be to use music streaming platforms, such as Spotify or Apple Music, to test whether consumers react differently when AI is disclosed naturally versus explicitly highlighted. Moreover, the study focuses on the negative impact of AI use, but does not explore potential positive effects, such as enhanced creativity or novel artistic styles that could arise. It would be particularly interesting to explore whether by

highlighting the potential benefits like innovation, personalization or efficiency AI can enhance consumer acceptance. Does emphasizing the novelty and creativity of AI-generated music enhance its appeal?

6. Conclusion

This thesis clarified critical barriers to the implementation and use of AI in the music industry and its impact on the consumer acceptance and examined the roles of transparency and trust in this relationship. The music industry, as a creative domain where human artistry intersects with technological innovation, offers a unique context for exploring how AI integration challenges traditional notions of creativity and authenticity. Presenting a significant skepticism by the consumer towards AI-created music, the findings reveal a negative impact on consumer acceptance. Contrary to the initial hypothesis stating that transparency mediates the relationship, transparency alone was not sufficient to mediate the negative relationship. Regardless, consumer trust in AI was found to play a crucial role as a moderator between the use of AI and consumer acceptance, with higher trust levels leading to less negative perceptions toward AI use.

AI in creative studies carries the potential to reshape the nature of artistic creation, raising questions about authorship, originality, and fairness. Consumers expect ethical standards that ensure AI does not overshadow human creativity or compromise the authenticity of the art they consume. The findings contribute to the ongoing complex discourse on how businesses and artists can try to implement AI into their creation process without alienating audiences and consumers. In today's increasingly by AI influenced environment this profound integration of AI will become necessary. Transparency in how AI is used is critical not only for ethical alignment but also for fostering trust in how technology supports, rather than replaces, human artistry. Supporting this, the findings suggest that strengthening consumer trust through strategic communication, ethical guidelines, and clear narratives about AI technology may be a very effective way to enhance consumers attitude and acceptance towards AI, probably more effective than only focusing on enhancing transparency. Enhancing ethical and transparent use of AI and educating the consumer about the technology, its possibilities, and how collaboration takes place is necessary to maintain and enhance ethical standards. By contributing to an emerging number of literature on AI acceptance especially within creative industries such as

the music industry, this study explores ideas for future research, such as longitudal studies. It suggests to deep dive into additional mediating and moderating factors, such as emotional perceptions and authenticity of AI-created content, to understand the consumer's perceptions on a deeper level.

To conclude, this thesis is stressing the fact that AI can potentially enhance creative processes when implemented carefully and under ethical guidelines that don't miss to address concerns arising with consumers. Since AI is gaining increasingly importance in the music industry and other creative industries, this analysis is offering detailed guidance on how to balance technological innovation with consumer acceptance. The aim should be to maintain the integrity of artistic expression by ensuring an enhancement with AI technologies rather than disrupting and substituting human creativity and artistry.

7. Appendix

Appendix 1: Survey Questionnaire

Block: Introduction

The purpose of this survey is to explore people's perceptions and preferences regarding different approaches in music creation. Please note that your answers are completely anonymous and will only be used for research purposes. There are no right or wrong answers, so we encourage you to respond honestly. This survey should take about E minutes to complete. Thank you for your time and valuable input!

Block: Trust in AI

Q1. I am open to listening to music that was created entirely or partially by AI.
Q2. I trust AI can competently create music that is enjoyable and of high quality.
Q3. I trust that AI understands what listeners like and can create music that matches audience preferences.
Q4. I trust that AI technology used in music creation is developed with ethical and safe practices in mind.
QE. I feel there is little risk of acting unethical when listening to music produced by AI.

Block: Scenarios

Scenario 1: Imagine a popular new song has been released. This song was created using advanced AI technology, with AI tools playing a significant role in the composition and production of the music.

Scenario 2: Imagine a popular new song has been released. This song was created entirely by human musicians and producers without any AI involvement in the composition or production.

Block: Scenario Presentation and Scenario–Based Questions (AI)

Q1. I believe that an AI–created song can be as high–quality as a song created by human artists.
Q2. I believe that an AI–created song can be as authentic and original as a song created by human artists.
Q3. I believe that an AI–created song is as emotional as a song created by human artists.
Q4. I would be likely to purchase or stream this song.
QE. Knowing that AI was used to create this song affects my enjoyment of it positively.
Q6. I would support artists or platforms that use AI in the creation process for future music.

Block: Scenario Presentation and Scenario–Based Questions (Non–AI)

Q1. I believe that a song created by human artists can be as high−quality as a song created by AI.
Q2. I believe that a song created by human artists can be as authentic and original as a song created by AI.
Q3. I believe that a song created by human artists is as emotional as a song created by AI.
Q4. I would be likely to purchase or stream this song.
QE. Knowing that human artists created this song affects my enjoyment of it positively.
Q6. I would support artists or platforms that don't use AI in the creation process for future music.

Block for AI and Non−AI

Q7. What are your reasons for supporting / not supporting artists that use AI in music creation?

Attention Check: To make sure you are paying attention, please select 'Strongly Disagree' for this statement.

Block: Transparency Perceptions

Q1. I am more likely to listen to AI−created music if I am informed about how AI was used in the creative process.
Q2. Artists and producers should always disclose when AI has been involved in creating a piece of music.
Q3. Knowing the extent of AI involvement in music creation would increase my enjoyment of the music.
Q4. I would be more inclined to purchase or stream a song if I had transparency about AI's role in its creation.
QE. What level of transparency would you prefer from artists/producers regarding the use of AI in music creation?

Block: Demographics

Q1. How old are you?
Q2. What is your gender?
Q3. What is your highest level of education?
Q4. How often do you listen to music?
QE. Which platforms do you primarily use to listen to music? (Select all that apply)
Q6. What genres of music do you typically enjoy listening to?
Q7. How familiar are you with the concept of AI−created music, where artificial intelligence assists in composing or producing songs?

Appendix 2: Variable Creation (R-Code)

```r
#Numeric Trust Items
data_1[c("trust_1", "trust_2", "trust_3", "trust_4", "trust_5")] <-
  lapply(data_1[c("trust_1", "trust_2", "trust_3", "trust_4", "trust_5")], function(x) as.numeric(as.character(x)))

#Trust Variable (average trust items)
data_1$trust <- rowMeans(data_1[c("trust_1","trust_2","trust_3","trust_4","trust_5")])

#Numeric Transparency Items
data_1[c("transparency_1", "transparency_2", "transparency_3", "transparency_4", "transparency_5")] <-
  lapply(data_1[c("transparency_1", "transparency_2", "transparency_3", "transparency_4", "transparency_5")], function(x) as.numeric(as.character(x)))

#Transparency Variable (average transparency items)
data_1$transparency <- rowMeans(data_1[c("transparency_1","transparency_2","transparency_3","transparency_4","transparency_5")])

#Numeric AI Items
data_1[c("ai_1", "ai_2", "ai_3", "ai_4", "ai_5", "ai_6")] <-
  lapply(data_1[c("ai_1", "ai_2", "ai_3", "ai_4", "ai_5", "ai_6")], function(x) as.numeric(as.character(x)))

#AI Variable (average AI items)
data_1$AI <- rowMeans(data_1[c("ai_1", "ai_2", "ai_3", "ai_4", "ai_5", "ai_6")])

#Numeric Non AI Items
data_1[c("non_ai_1", "non_ai_2", "non_ai_3", "non_ai_4", "non_ai_5", "non_ai_6")] <-
  lapply(data_1[c("non_ai_1", "non_ai_2", "non_ai_3", "non_ai_4", "non_ai_5", "non_ai_6")], function(x) as.numeric(as.character(x)))

#Non AI Variable (average Non AI items)
data_1$Non_AI <- rowMeans(data_1[c("non_ai_1", "non_ai_2", "non_ai_3", "non_ai_4", "non_ai_5", "non_ai_6")])
```

Appendix 3: Cronbach's alpha (R-Code)

```r
#########################################################
########## CRONBACHS ALPHA ##############################
#########################################################
# Calculate Cronbach's alpha for Transparency
transparency_items <- data_1[c("transparency_1", "transparency_2", "transparency_3", "transparency_4", "transparency_5")]
str(transparency_items)
transparency_items[] <- lapply(transparency_items, function(x) as.numeric(as.character(x))) # only numeric values
colSums(is.na(transparency_items))  # Check NAs in transparency

transparency_alpha <- alpha(transparency_items) # calculate alpha
print(transparency_alpha)

# Calculate Cronbach's alpha for Trust
trust_items <- data_1[c("trust_1", "trust_2", "trust_3", "trust_4", "trust_5")]
str(trust_items)
trust_items[] <- lapply(trust_items, function(x) as.numeric(as.character(x)))
colSums(is.na(trust_items))  # Check NAs in trust

trust_alpha <- alpha(trust_items)
print(trust_alpha)

# Calculate Cronbach's aplha for Acceptance variables (ai and nonai group)
# Subset the acceptance items
ai_items <- data_1[c("ai_1", "ai_2", "ai_3", "ai_4", "ai_5", "ai_6")]
non_ai_items <- data_1[c("non_ai_1", "non_ai_2", "non_ai_3", "non_ai_4", "non_ai_5", "non_ai_6")]
# Convert items to numeric
ai_items[] <- lapply(ai_items, function(x) as.numeric(as.character(x)))
non_ai_items[] <- lapply(non_ai_items, function(x) as.numeric(as.character(x)))
# Handle missing values
ai_items <- na.omit(ai_items)
non_ai_items <- na.omit(non_ai_items)
# Impute missing values
ai_items[] <- lapply(ai_items, function(x) ifelse(is.na(x), mean(x, na.rm = TRUE), x))
non_ai_items[] <- lapply(non_ai_items, function(x) ifelse(is.na(x), mean(x, na.rm = TRUE), x))
# Cronbach's alpha for AI group
alpha_ai <- alpha(ai_items)
print(alpha_ai)
# Cronbach's alpha for Non-AI group
alpha_non_ai <- alpha(non_ai_items)
print(alpha_non_ai)
```

Appendix 4: Normal Regression – Testing H1 (R-Code)

```
############################################################
########## NORMAL REGRESSION (H1) ##########################
############################################################
#normal Regression Use of AI-Consumer Acceptance.
AIACCEPT <- lm(AI_combined ~ use_of_ai + familiarity + regularity_num + dgender + age + degree_num, data = data_1)
summary(AIACCEPT)

# Export Table
stargazer(AIACCEPT, type = "html", out = "regression_results_h1.html")
```

Appendix 5: Process Macro Model 4 – Testing H2 (R-Code)

```
#################################################################
########## PROCESS MACRO (H2 and H3) ############################
#################################################################
#Process macro Hayes Model 4 (H2)
#process (data = data_1, y = "AI", x = "use_of_ai", m = "transparency")
#process Model 4 without covariates
process(data = data_1, y = "AI_combined", x = "use_of_ai", m = "transparency", model = 4,
        effsize = 1, total = 1, stand = 1,
        boot = 10000, modelbt = 1, seed = 42)

#process Model 4 with covariates (final version)
process(data = data_1, y = "AI_combined", x = "use_of_ai", m = "transparency", model = 4,
        effsize = 1, total = 1, stand = 1,
        cov = c("familiarity", "regularity_num", "dgender", "age", "degree_num"),
        boot = 10000, modelbt = 1, seed = 42)
```

Appendix 6: Process Macro Model 15 – Testing H3 (R-Code)

```
#Process macro Hayes Model 15 (H3)
#process (data = data_1, y = "AI", x = "use_of_ai", m = "transparency", w = "trust")
#process Model 15 without covariates
process(data = data_1, y = "AI_combined", x = "use_of_ai", m = "transparency", w = "trust", model = 15,
        effsize = 1, total = 1, stand = 1,
        boot = 10000, modelbt = 1, seed = 42)

#process Model 15 with covariates (final version)
process(data = data_1, y = "AI_combined", x = "use_of_ai", m = "transparency", w = "trust", model = 15,
        effsize = 1, total = 1, stand = 1,
        cov = c("familiarity", "regularity_num", "dgender", "age", "degree_num"),
        boot = 10000, modelbt = 1, seed = 42)
```

Appendix 7

Table 8. Results for the outcome variable transparency in Model 4.

	Coefficient	SE	t	p	LLCCI	ULCI
Constant	E.0801***	1.0323	4.9213	0.0000	3.0408	7.119E
Use of AI	0.2962	0.1622	1.8266	0.0697	−0.0242	0.6166
Familiarity	0.0743	0.0487	1.E2E3	0.1293	−0.0219	0.170E
Regularity	−0.0371	0.1874	−0.1980	0.8433	−0.4073	0.3331
Gender	0.2770	0.16E7	1.671E	0.0967	−0.0E04	0.6043
Age	−0.0077	0.0063	−1.2304	0.2204	−0.0201	0.0047
Degree	−0.0761	0.0762	−0.9991	0.3193	−0.2266	0.0744

***$p < 0.01$

Note: LL=lower limit. UL=upper limit. CI=confidence interval.

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