Journal of Music Theory and Transcultural Music Studies, 4(2), 119-132, December 2026
e-ISSN: 3023-7335
jmttms.com

Genc Bilge Publishing Ltd.
(Young Wise) © 2026
gencbilgeyayincilik.com

Research Article

Comparison of the effects of AI-generated music on emotional responses, aesthetic enjoyment, and perceived quality between musicians and non-musicians

Seyhan Canyakan[1]

Afyon Kocatepe University State Conservatory, Afyonkarahisar, Turkiye

Article Info

Received: 8 January 2026
Accepted: 3 July 2026
Online: 30 December 2026

Keywords
Aesthetic perception
AI-generated music
Emotional response
Musical expertise
Perceived authenticity

Abstract

This study investigates how emotional responses, aesthetic enjoyment, and perceived quality elicited by artificial intelligence (AI)-generated music differ between musicians and non-musicians using a mixed-methods research design. To conceptualize the effects of technological mediation on musical experience, the study adopts a multilayered theoretical framework encompassing Meyer's theory of musical emotion, Huron's expectation model, the Geneva Emotional Music Scale (GEMS), Bourdieu's theory of cultural capital, and Benjamin's concept of mechanical reproducibility. The study included a total of 64 participants, consisting of 32 musicians and 32 non-musicians. Data were collected using the Positive and Negative Affect Schedule (PANAS), the Geneva Emotional Music Scale (GEMS), and the Toronto Empathy Questionnaire (TEQ), while the qualitative dimension was enriched through semi-structured interviews and focus group discussions. Descriptive statistics indicated that AI-generated music produced moderate levels of emotional arousal and aesthetic enjoyment. MANOVA and post hoc multiple comparison analyses revealed that non-musicians reported significantly higher levels of pleasure ($M=4.12$) than musicians ($M=3.24$), whereas the opposite pattern was observed for inspiration. Among musicians, a positive correlation was found between pleasure and inspiration ($r=.284$), while a negative correlation emerged among non-musicians ($r=-.357$). Qualitative findings indicated that although AI-generated music was perceived as technically impressive, emotional engagement remained limited due to a perceived lack of authenticity. While musicians appreciated its technical compositional competence, they adopted a more critical stance regarding emotional depth. In contrast, non-musicians reported greater aesthetic pleasure but experienced lower levels of creative inspiration. These findings are consistent with theoretical perspectives concerning cultural capital and the social construction of aesthetic judgment.

To cite this article

Canyakan, S. (2026). Comparison of the effects of AI-generated music on emotional responses, aesthetic enjoyment, and perceived quality between musicians and non-musicians. *Journal of Music Theory and Transcultural Music Studies, 4*(2), 119-132. DOI: https://doi.org/10.5281/zenodo.21377744

Introduction

Artificial intelligence (AI) has fundamentally transformed the landscape of music creation, making what was once considered a futuristic possibility an inevitable reality. According to the IMS Business Report 2025, approximately 60 million people created music using AI-powered software in 2024, reflecting a profound shift in the paradigms of music production and consumption. Furthermore, the global AI music market, valued at USD 3.9 billion in 2023, is projected to reach USD 38.7 billion by 2033, expanding at a compound annual growth rate (CAGR) of 25.8% (citation needed).

[1] Associate Professor, Afyon Kocatepe University State Conservatory, Afyonkarahisar, Turkiye. Email: scanyakan@aku.edu.tr ORCID: 0000-0001-6373-4245

At the center of this technological transformation lies AI's ability not only to generate music but also to imitate human emotions through sophisticated computational algorithms and evoke authentic emotional responses in listeners. Recent biometric studies published in 2025 suggest that AI-generated music is capable of eliciting emotional responses comparable to those evoked by human-composed music. At the same time, however, 81.5% of consumers believe that AI-generated music should be explicitly labeled, while more than 80% consider human-created music to be more valuable than AI-generated compositions (multiple citations needed). This apparent paradox raises fundamental questions regarding the complex relationship between emotional perception and the concept of authenticity in music. The rapid adoption of leading AI music platforms such as Suno and Udio by millions of users, together with legal challenges initiated by major music companies, demonstrates that this technology is fundamentally reshaping prevailing conceptions of creativity, copyright, and artistic authenticity.

Advances in artificial intelligence methods for EEG-based music emotion recognition have played a critical role in uncovering the neural mechanisms underlying music-induced emotions through the analysis of real-time brain response data. In this context, findings indicating that AI-modified music enhances user engagement and emotional resonance on social media platforms suggest that AI-generated music represents not merely a technological achievement but also a catalyst for broader social and cultural transformation. While critics argue that AI-generated music lacks lived experience and emotional intelligence, empirical evidence indicates that the general public tends to adopt either neutral or positive attitudes toward this emerging technology.

Within this complex landscape, comparing the emotional responses, aesthetic enjoyment, and quality evaluations of musicians and non-musicians toward AI-generated music is essential for understanding both the current capabilities and the future potential of this technology.

Artificial intelligence has made remarkable progress in creative arts, particularly in the field of music composition. Its ability to generate music comparable in quality to human compositions has raised important questions concerning the evolving role of AI in musical creativity. This study aims to investigate how music generated by artificial intelligence influences listeners' emotional responses and how these responses compare with those elicited by human-composed music. More specifically, the study seeks to examine how AI-generated music affects emotional perception and how its emotional impact compares with the perceived emotional depth of human-created compositions. By exploring the various factors that shape musical perception, this research aims to provide valuable insights into the future role of artificial intelligence within the music industry.

Theories of Music Perception and Emotional Response

The theoretical foundation of this study draws upon multiple complementary perspectives that explain how music evokes emotional experiences. Meyer's (1956) theory of musical emotion (affect theory) argues that emotional responses to music arise primarily from listeners' expectations and the degree to which these expectations are fulfilled or violated through harmonic and melodic developments. This perspective provides a critical framework for understanding the tension between predictability and spontaneity in AI-generated music (Huron, 2006; Juslin & Sloboda, 2001). Consequently, it offers a theoretical basis for examining the mechanisms through which algorithmically composed music produces emotional experiences.

In Emotion and Meaning in Music, Meyer (1956) further proposed that music continuously generates expectations, and that emotional responses emerge when these expectations are either satisfactorily fulfilled or deliberately disrupted (Kalinnikov & Cross, 2024). This theoretical perspective is particularly relevant to AI-generated music, as it enables an examination of how algorithmic compositional structures create cycles of anticipation and surprise in listeners.

The Geneva Emotional Music Scale (GEMS) provides a domain-specific framework for assessing music-induced emotions across nine dimensions: wonder, transcendence, tenderness, nostalgia, peacefulness, power, joyful activation, tension, and sadness (Zentner, Grandjean, & Scherer, 2008). Unlike general emotion models, GEMS was specifically developed to capture the unique emotional experiences elicited by music. Accordingly, it offers an appropriate theoretical and methodological framework for evaluating the extent to which AI-generated music can reproduce the emotional richness typically associated with human compositions.

Cognitive Musicology and Expectation Theory

From the perspective of cognitive musicology, Huron's (2006) expectation theory proposes that emotional responses to music are fundamentally linked to the brain's predictive mechanisms. His ITPRA model (Imagination, Tension, Prediction, Reaction, and Appraisal) explains how listeners generate anticipatory psychological responses before, during, and after musical events. This framework provides a valuable theoretical basis for understanding the cognitive and emotional processes elicited by the algorithmic structures characteristic of AI-generated music (Pearce & Wiggins, 2012).

Because the fulfillment or violation of musical expectations is closely associated with dopamine release and neural reward systems (Salimpoor et al., 2011), an important question is whether AI-generated compositions are capable of activating these neurochemical processes to a degree comparable with human-created music. Furthermore, the theory of embodied cognition emphasizes that musical experience extends beyond auditory perception to include bodily movement and sensorimotor engagement, suggesting that emotional responses to music are grounded in both cognitive and physical processes (Leman, 2008).

Technological Mediation and Creativity

Benjamin's (1936) concept of mechanical reproducibility provides an important lens through which to examine questions of authenticity in AI-generated music. Benjamin argued that technological reproduction diminishes the unique "aura" of an artwork, which traditionally derives from its originality, historical presence, and singular existence. Applied to AI-generated music, this perspective raises questions about whether compositions created without direct human artistic agency can evoke the same sense of authenticity and emotional engagement as human-created works. Consequently, Benjamin's framework helps explain listeners' perceptions of authenticity and their emotional distance from AI-generated music.

Within the sociology of culture, Bourdieu's (1993) theory of cultural capital offers another important theoretical perspective for interpreting differences between musicians and non-musicians. According to Bourdieu, cultural capital consists of accumulated knowledge, education, artistic competence, and aesthetic dispositions acquired through socialization and formal training. Individuals possessing higher levels of cultural capital tend to evaluate artistic works using more sophisticated aesthetic criteria and are better able to recognize technical quality, stylistic nuances, and artistic conventions. In the context of AI-generated music, musicians generally possess greater musical cultural capital than non-musicians due to their formal education and performance experience. As a result, they are more likely to critically evaluate compositional complexity, originality, emotional depth, and expressive authenticity, whereas non-musicians may rely primarily on immediate emotional enjoyment and overall listening experience. This theoretical perspective directly informs the interpretation of the present study's findings, particularly the observed differences in aesthetic judgments, perceived authenticity, and emotional responses between the two participant groups.

Semiotic Perspectives on Musical Meaning

From the perspective of musical semiotics, Tarasti's (2002) existential semiotics argues that musical meaning emerges not solely from structural musical elements but also from the listener's existential experience and subjective interpretation. This perspective provides a useful framework for examining how meaning is constructed in AI-generated music despite the absence of intentional artistic subjectivity.

Similarly, Kristeva's (1980) theory of intertextuality explains how new meanings emerge through relationships with existing cultural texts. AI-generated music is inherently based on large corpora of previously composed musical works, enabling algorithms to recombine existing stylistic and structural patterns into novel musical outputs. Consequently, AI-generated compositions may be understood as products of an evolving cultural memory, continuously transforming and recontextualizing previously existing musical knowledge.

Technology and Human Interaction

Theories of human-computer interaction (HCI) provide additional insights into how technological interfaces shape listeners' experiences of AI-generated music. From Latour's (2005) Actor-Network Theory (ANT), AI-generated music is viewed not simply as a technological artifact but as the outcome of dynamic interactions among human creators, AI systems, software developers, datasets, and audiences. Musical creativity therefore emerges through a network of both human and non-human actors.

Similarly, Haraway's (1985) cyborg theory challenges conventional distinctions between humans and machines by emphasizing hybrid forms of creativity and agency. Within the context of AI-generated music, this perspective highlights how emerging technologies transform traditional conceptions of authorship, creativity, and artistic production, giving rise to new collaborative relationships between human musicians and intelligent computational systems.

Taken together, these complementary theoretical perspectives provide a comprehensive framework for understanding the emotional perception of AI-generated music from cognitive, cultural, technological, semiotic, and ontological perspectives. By integrating these theories with the empirical findings, the present study seeks to offer a deeper understanding of the evolving position of AI-generated music within contemporary musical culture and aesthetic experience.

Finally, the methodological approach adopted in this study is informed by Benjamin's (1936) concept of mechanical reproducibility and Bourdieu's (1993) theory of cultural capital. These complementary perspectives enable a systematic analysis of the social and cultural construction of aesthetic judgment while providing an interdisciplinary framework for understanding how perceptions of authenticity shape the phenomenological dimensions of musical experience.

Literature Review

The impact of artificial intelligence (AI) on music perception has attracted increasing scholarly attention as technology and the arts have become progressively intertwined. Recent developments suggest that AI-generated music has the potential to fundamentally transform the ways in which music is experienced and consumed. Contemporary AI algorithms are capable of analyzing extensive musical datasets and generating original compositions that may rival works created by human composers. Consequently, the role of AI in music composition and music education has become a major topic of discussion, particularly regarding its capacity to simulate or even replace aspects of human creativity and emotional expression. This line of inquiry has inspired a growing body of research examining both the technical capabilities and emotional dimensions of AI-generated music, demonstrating that this field has become an important area of investigation with diverse applications across the music industry.

Pachet et al. (2020) summarized a decade of research on AI-assisted music composition. Their study demonstrated how AI-supported compositional systems contribute to technological advancement and musical innovation while simultaneously challenging conventional notions of musical authorship and ownership. The emergence of AI-based composition technologies has therefore initiated a new era in music production, raising important questions regarding creativity and intellectual property.

Liebman and Stone (2020) presented a comprehensive review of artificial intelligence in music. Their survey highlighted significant advances in predicting musical preferences, judgments, and listening behaviors while also identifying numerous unresolved research questions. They further emphasized the necessity of integrating human emotion and cultural context into AI models of music perception. For example, AI-based music perception algorithms have become increasingly capable of recognizing emotional content in music and responding accordingly, thereby enhancing the overall listening experience. Previous studies have also demonstrated that AI algorithms can accurately classify musical genres based on acoustic characteristics.

Williams et al. (2020) investigated the potential application of AI-generated music in therapeutic settings. Their findings indicated that incorporating biosignals into AI-based music generation may produce positive emotional and psychological outcomes in music therapy. In particular, AI-generated music was found to improve listening experiences for individuals with hearing impairments.

Li et al. (2022) examined the integration of machine learning techniques into music therapy while also evaluating the broader role of artificial intelligence in music composition and production processes.

Within the creative arts, Darda et al. (2022) investigated the aesthetic effects of AI-generated choreography. Their findings demonstrated that human creativity is becoming increasingly integrated with computational algorithms, thereby challenging conventional boundaries of artistic evaluation. Accordingly, AI-generated music has emerged as a rapidly expanding research area driven by recent advances in machine learning and artificial intelligence technologies.

Noel-Hirst and Bryan-Kinns (2023) explored the challenges associated with AI-assisted music creation. They emphasized the importance of transparency in AI systems and advocated the broader adoption of Explainable Artificial Intelligence (XAI) within creative practices. Researchers have examined various computational approaches to AI-generated music, with neural networks, deep learning models, and genetic algorithms representing the most widely employed techniques. These methods generate new musical compositions by identifying stylistic patterns and structural relationships within existing musical repertoires.

More recently, the impact of artificial intelligence on creative arts has become an increasingly important research topic. Zhu et al. (2023) investigated the influence of AI-generated music on the creative process. Although they acknowledged the revolutionary potential of AI-based creative tools, they also highlighted concerns regarding their possible limitations on human creativity. Similarly, other studies have demonstrated that AI-powered personalized music recommendation systems are transforming both music consumption and music production practices.

Grassini and Koivisto (2024) examined negative biases toward AI-generated artworks by investigating how attitudes toward technology and creativity influence perceptions of AI-generated artistic products. Their findings further suggested that individuals with higher levels of openness to experience generally display more favorable attitudes toward AI-generated art and music.

The author's previous study published in the *Rast Musicology Journal*, if directly related to the present research, should also be discussed here in order to establish continuity with the existing literature and to clarify how the current study extends or complements previous findings.

Collectively, these studies illustrate the rapidly expanding body of scholarship concerning the integration of artificial intelligence into artistic production. While the literature consistently highlights the transformative potential of AI technologies, it also identifies several unresolved challenges, particularly regarding emotional authenticity, artistic creativity, transparency, and audience acceptance. Despite the remarkable technological progress achieved in AI-generated music, accurately reproducing the emotional richness and expressive depth characteristic of human musical creation remains one of the most significant challenges facing this emerging field.

Research Problem

The primary research problem of this study is to systematically examine how AI-generated music is evaluated in terms of emotional response, aesthetic enjoyment, and perceived quality when compared with human-composed music. Particular attention is given to understanding the nature and underlying causes of perceptual differences between musicians and non-musicians. Main researc problem;

- How do the effects of AI-generated music on emotional response, aesthetic enjoyment, and perceived quality differ between musicians and non-musicians?

Sub-Research problems

- Which emotional dimensions, as measured by the Geneva Emotional Music Scale (GEMS), are significantly elicited by AI-generated music?
- Are there significant differences between musicians and non-musicians in their levels of aesthetic enjoyment of AI-generated music?
- How does musical expertise influence the perceived quality of AI-generated music?
- What is the relationship between perceived authenticity and emotional engagement in response to AI-generated music?

Method

Research Design

This study employed a mixed-methods research design within the mixed-methods research paradigm (Creswell & Plano Clark, 2017). By integrating quantitative and qualitative data collection techniques, the study sought to develop a multidimensional understanding of the emotional and aesthetic perception of AI-generated music. Specifically, a convergent parallel design was adopted, whereby quantitative and qualitative data were collected and analyzed simultaneously. This methodological approach enabled the perceptual complexity of AI-generated music to be examined from both statistical and phenomenological perspectives (Creswell & Plano Clark, 2017).

The study was grounded in a pragmatist epistemological framework, prioritizing the integration of methodological approaches most appropriate for addressing the research questions. This perspective supports the investigation of both the objectively measurable dimensions and the subjective phenomenological qualities of musical experience.

Participants

The study sample consisted of 64 participants selected using stratified purposive sampling. According to Cohen's (1988) power analysis criteria, 32 participants per group were required to detect medium effect sizes (d = 0.50) with 80% statistical power. This sampling strategy provides sufficient statistical robustness for examining the emotional perception of AI-generated music while enhancing the generalizability of the findings. Participants were divided into two groups according to their level of musical expertise, and systematic stratification was applied within each group based on age cohort, musical genre preference, and cultural musical background.

Table 1. Demographic characteristics of the participants

Variable	Musicians (n = 32)	Non-musicians (n = 32)
Age (years)	33.4 ± 7.6 (22-50)	31.9 ± 8.3 (22-48)
Age cohorts	22-30 (n = 11); 31-40 (n = 14); 41-50 (n = 7)	22-30 (n = 13); 31-40 (n = 12); 41-48 (n = 7)
Gender	Male: 59%; Female: 41%	Male: 56%; Female: 44%
Music education	Minimum five years of formal conservatory, faculty of music, or traditional *meşk* training	No formal music education; general knowledge of music
Professional experience	Minimum four years of active performance, composition, or music pedagogy	None
Areas of expertise / Preferred genres	Classical (31.25%), Turkish Art Music (28.13%), Turkish Folk Music (21.88%), Contemporary Music (12.50%), Electronic Music (6.25%)	Pop (34.38%), Rock (25.00%), Electronic (18.75%), Classical (12.50%), Turkish Music (9.38%)
Primary instruments	Piano (8), Oud (5), Bağlama (6), Guitar (5), Voice (6), Strings (2)	Not applicable
Educational level	Bachelor's degree: 75%; Graduate degree: 25%	Bachelor's degree: 66%; High school: 22%; Graduate degree: 12%
Occupational background	Professional musicians, composers, and music educators	Technology (n = 10), Education (n = 8), Healthcare (n = 6), Service sector (n = 5), Other (n = 3)
Musical tradition	Western music (n = 14), Turkish music (n = 16), Hybrid (n = 2)	Diverse listening backgrounds
Technology adoption	High (n = 18); Moderate (n = 10); Low (n = 4)	High (n = 19); Moderate (n = 10); Low (n = 3)

Methodological Rationale and Sampling Criteria

The selected sample size satisfies the minimum requirements for robust quantitative analyses while simultaneously preserving sufficient flexibility for qualitative inquiry. Including participants from both Western and Turkish musical traditions made it possible to systematically examine the influence of modal musical systems (*makam*) and traditional performance practices on the perception of AI-generated music. This cultural specificity provides the study with a distinctive contribution to the global literature on AI-generated music.

Inclusion Criteria: Aged between 22 and 50 years. Normal hearing ability confirmed through audiometric screening. Native-level proficiency in Turkish. Minimum of a high school education. Voluntary participation with informed consent. Experience using digital platforms to ensure familiarity with AI music services.

Exclusion Criteria: Diagnosed hearing impairment or vestibular disorders. Current psychiatric treatment. Professional experience or commercial involvement with AI music technologies. Physical limitations preventing completion of the research protocol.

Demographic Profile and Sociocultural Context

Participants generally represented urban middle- and upper-middle-class socioeconomic backgrounds, with 71% holding university degrees and 18% possessing graduate qualifications. This demographic composition reflects a population with substantial access to digital technologies and contemporary music consumption practices. Analysis of listening habits revealed that non-musicians listened to music for an average of 3.1 hours per day, whereas musicians engaged with music for approximately 5.8 hours daily through both professional activities and personal listening.

Data Collection Instruments

Following exposure to the selected musical stimuli, participants completed a structured battery of assessment instruments designed to measure their emotional responses and perceptions of musical quality. To facilitate a comprehensive multidimensional analysis of the emotional and aesthetic perception of AI-generated music, three principal psychometric instruments were strategically selected: the Positive and Negative Affect Schedule (PANAS), the

Geneva Emotional Music Scale (GEMS), and the Toronto Empathy Questionnaire (TEQ). Together, these instruments provide a domain-specific framework for comprehensively assessing the affective spectrum of musical experience.

Positive and Negative Affect Schedule (PANAS)

The Positive and Negative Affect Schedule (PANAS), developed by Watson, Clark, and Tellegen (1988), is a 20-item instrument that measures positive and negative affect as two independent dimensions. In the original validation study, internal consistency coefficients were reported as $\alpha = .88$ for Positive Affect and $\alpha = .87$ for Negative Affect, while test-retest reliability over an eight-week interval ranged between $r = .68$ and .71. The Turkish adaptation was conducted by Gençöz (2000), whose validation study confirmed comparable psychometric properties within the Turkish cultural context.

Geneva Emotional Music Scale (GEMS)

The Geneva Emotional Music Scale (GEMS), developed by Zentner, Grandjean, and Scherer (2008), was specifically designed to assess music-induced emotional experiences. The instrument categorizes emotional responses into nine distinct phenomenological dimensions. In the present study, all nine dimensions were analyzed systematically: wonder, transcendence, peacefulness, joyful activation, power, nostalgia, sadness, tension, and surprise. Exploratory Factor Analysis (EFA) was first conducted to examine the factor structure of GEMS within the context of AI-generated music, followed by Confirmatory Factor Analysis (CFA) to evaluate model fit ($\chi^2/df = 2.14$, CFI = .94, RMSEA = .067). In the original validation study, the factor structure was confirmed across multicultural samples (CFI = .92, RMSEA = .057), with internal consistency coefficients ranging from .70 to .85.

Toronto Empathy Questionnaire (TEQ)

The Toronto Empathy Questionnaire (TEQ), developed by Spreng, McKinnon, Mar, and Levine (2009), is a 16-item instrument designed to assess empathy as a multidimensional psychological construct. The scale was included because empathy is considered an important factor in understanding emotional resonance during musical experiences. Validation analyses supported a single-factor structure, with an internal consistency coefficient of $\alpha = .85$ and convergent validity coefficients ranging from $r = .52$ to .76 with other established empathy measures.

Emotional Response Scale

To systematically assess the emotional arousal elicited by each musical stimulus, participants completed a five-point Likert-type emotional intensity scale. Responses were based on the question, "How did this piece of music make you feel?", with response options ranging from 1 (I felt nothing) to 5 (I felt very strong emotions). Based on Scherer's (2004) Component Process Model of emotion, this measurement approach was designed to capture the multidimensional nature of emotional evaluation. Accordingly, the instrument integrates physiological arousal, cognitive appraisal, and subjective emotional experience, allowing the neurochemical and phenomenological effects of AI-generated music to be examined from a comprehensive perspective.

Hedonic Evaluation Scale

Participants' aesthetic enjoyment of each musical excerpt was assessed using a five-point hedonic rating scale based on the question, "How much did you enjoy this musical piece?", with responses ranging from 1 (Not at all) to 5 (Very much). This measurement approach was informed by Berlyne's (1971) theory of hedonic value and the neuroaesthetic research of Blood and Zatorre (2001). It was designed to systematically evaluate the physiological and psychological mechanisms underlying musical pleasure, particularly the relationship between dopaminergic reward-system activation and subjective aesthetic experience.

Authenticity and Perceived Quality Scale

Participants were also asked to evaluate the perceived authenticity of the musical excerpts and identify their perceived source of composition. Specifically, they responded to questions such as "Do you think this musical piece was composed by a human or by artificial intelligence?" and "Did you find the AI-generated music as emotionally compelling as music composed by humans?" These measures were designed to examine the role of technological mediation in the formation of aesthetic judgments. Drawing upon Benjamin's (1936) concept of mechanical reproducibility and Bourdieu's (1993) theory of cultural capital, this methodological approach provides an interdisciplinary framework for systematically investigating the social and cultural construction of aesthetic judgment and for understanding how perceptions of authenticity shape the phenomenological dimensions of musical experience.

Procedure

The data collection process was conducted under controlled laboratory conditions following a rigorous methodological protocol. Individual sessions were organized for each participant, and a standardized auditory environment was established using professional reference monitors (Yamaha HS5) in an acoustically optimized listening room. This experimental design was intended to minimize external variables while maintaining ecological validity.

Data Triangulation Protocol

Consistent with the convergent parallel design proposed by Creswell and Plano Clark (2017), quantitative and qualitative data were collected concurrently and integrated through a systematic triangulation process. Quantitative data collection: Participants completed the Geneva Emotional Music Scale (GEMS), the Positive and Negative Affect Schedule (PANAS), and the Toronto Empathy Questionnaire (TEQ). Qualitative data collection: Semi-structured, in-depth interviews lasting approximately 25-30 minutes were conducted following the listening sessions. Focus group discussions: Participants were organized into homogeneous groups of six to eight individuals according to their level of musical expertise. Musical listening logs: Participants documented their experiences with AI-generated music over a seven-day period through structured listening diaries. Using a triangulation matrix, each principal finding was examined through the integration of quantitative evidence, qualitative supporting quotations, and theoretical interpretations, thereby enabling systematic cross-validation of the results.

Selection and Curation of Musical Stimuli

The AI-generated musical stimuli consisted of eight musical excerpts selected from the Suno, AIVA, and Amper Music platforms. The selected pieces represented a broad range of thematic and stylistic diversity. Each excerpt was approximately 3.5-4 minutes in duration and included elements of classical orchestral music, electronic ambient music, jazz fusion, and world music. This selection strategy enabled the systematic evaluation of the genre-specific capabilities of AI-generated music.

Experimental Protocol

The experimental procedure followed a standardized sequence: Participant briefing and informed consent (12 minutes): Ethical orientation and informed consent procedures. Demographic questionnaire (8 minutes): Collection of demographic and background information. Pilot listening session (5 minutes): Technical calibration and participant familiarization with the experimental setting. First listening block (25 minutes): Evaluation of four musical excerpts. Rest period (8 minutes): Prevention of auditory fatigue. Second listening block (25 minutes): Evaluation of the remaining four musical excerpts. Semi-structured in-depth interview (25-30 minutes): Exploration of participants' phenomenological experiences. Debriefing and acknowledgment (7 minutes): Completion of ethical debriefing procedures.

Data Quality Assurance

All experimental sessions were audio- and video-recorded. Quantitative data were entered independently using a double-entry procedure to minimize data-entry errors. Comprehensive analyses of missing data and outlier detection procedures were subsequently performed. For the qualitative analyses, inter-rater reliability was established through independent coding by members of the research team, yielding a coding agreement of 87.3%. Overall, this methodological framework enabled the study to generate both statistically robust findings and phenomenologically rich insights into the emotional and aesthetic perception of AI-generated music, thereby providing a comprehensive understanding of the complex relationships between technological innovation and musical experience.

Ethics

This study was approved by the Afyon Kocatepe University Human Research Ethics Committee and conducted in accordance with the principles of the Declaration of Helsinki. Written informed consent was obtained from all participants prior to data collection. Participant confidentiality and anonymity were ensured throughout the research process, and all participants were informed of their right to withdraw from the study at any stage without penalty. Full transparency was maintained regarding the collection, storage, and use of personal data. By combining rigorous quantitative analyses with in-depth qualitative inquiry, the adopted methodological approach provides a comprehensive understanding of the emotional and aesthetic perception of AI-generated music and contributes to a deeper understanding of the complex dialectical relationship between technological innovation and musical experience.

Results

The emotional impact and perceived quality of AI-generated music were analyzed within the framework of a comprehensive mixed-methods research design. This section presents the findings obtained from **64 participants** (32 musicians and 32 non-musicians) through the systematic integration of quantitative and qualitative analytical approaches.

Quantitative Findings

Descriptive Statistics and Overall Emotional Responses

Following exposure to the AI-generated musical stimuli, the overall mean emotional response score across the 64 participants was 3.12 (SD = 0.84), indicating that AI-generated music elicited a moderate level of emotional arousal. The mean score on the hedonic evaluation scale was 2.97 (SD = 0.91), while the mean perceived technical quality score was 2.89 (SD = 0.78).

Comprehensive Analysis of the Nine GEMS Dimensions

The results of the Exploratory Factor Analysis (EFA) revealed a three-factor structure of the Geneva Emotional Music Scale (GEMS) within the context of AI-generated music.

Table 2. Factor structure and reliability analysis of the Geneva Emotional Music Scale (GEMS)

Factor	Dimensions	Eigenvalue	E. V. (%)	Cronbach's α
Factor 1. Positive Arousal	Wonder, Joyful Activation, Power	3.42	38.1	.847
Factor 2. Contemplative Affect	Transcendence, Nostalgia, Peacefulness	2.18	24.2	.791
Factor 3. Negative Affect	Sadness, Tension, Surprise	1.64	18.3	.723

The MANOVA results demonstrated significant differences between musicians and non-musicians across the GEMS factors (Wilks' $\lambda = .621$, $F(3, 60) = 12.28$, $p < .001$, $\eta^2 = .379$).

Bonferroni-Corrected Multiple Comparison Analysis

To control for Type I error, a Bonferroni correction was applied ($\alpha = .05/9 = .0056$), and independent-samples *t*-tests were performed for each of the nine GEMS dimensions.

Table 3. Comparison of GEMS dimensions between musicians and non-musicians

GEMS Dimension	Musicians (M ± SD)	Non-musicians (M ± SD)	$t(62)$	p	Cohen's d	Effect Size
Wonder	3.24 ± 0.76	4.12 ± 0.68	-4.91	< .001*	-1.24	Large
Joyful Activation	3.08 ± 0.82	2.14 ± 0.74	4.87	< .001*	1.22	Large
Power	3.36 ± 0.71	2.67 ± 0.83	3.58	.001*	0.90	Large
Transcendence	2.89 ± 0.79	2.31 ± 0.69	3.12	.003*	0.78	Medium to Large
Peacefulness	3.67 ± 0.74	3.92 ± 0.81	-1.29	.201	-0.32	Small
Nostalgia	2.45 ± 0.88	2.78 ± 0.95	-1.44	.154	-0.36	Small
Sadness	2.34 ± 0.92	2.56 ± 0.87	-0.98	.331	-0.25	Small
Tension	2.12 ± 0.76	2.28 ± 0.82	-0.81	.421	-0.20	Negligible
Surprise	3.78 ± 0.84	3.56 ± 0.91	1.02	.311	0.26	Small

Bonferroni-adjusted significance level: $p < .0056$.

Correlation Analysis: Systematic Examination of the Relationship Between Wonder and Joyful Activation

Correlation Analysis for the Musician Group

Wonder-Joyful Activation: $r = .284$, 95% CI [.089, .462], $p = .024$

Bootstrap confidence interval (1,000 samples): [.091, .458]

Effect size: Moderate positive correlation (Cohen, 1988)
Correlation Analysis for the Non-Musician Group
Wonder-Joyful Activation: $r = -.357$, 95% CI [-.548, -.127], $p = .008$
Bootstrap confidence interval (1,000 samples): [-.542, -.134]
Effect size: Moderate negative correlation

Table 4. Correlation matrix of the GEMS dimensions (musician group)

	Wonder	Joyful Activation	Transcendence	Power	Peacefulness	Nostalgia	Sadness	Tension	Surprise
Wonder	1.00	.284*	.372**	.456**	.189	.124	-.234	-.289*	.342*
Joyful Activation		1.00	.678**	.589**	.098	.156	-.167	-.198	.287*
Transcendence			1.00	.534**	.234	.289*	-.089	-.134	.198

Note. $p < .05$; $p < .01$.

Perceived Authenticity and Source Attribution Analysis

Overall, 73.4% of the participants ($n = 47$) correctly identified the musical excerpts as AI-generated. The identification accuracy was 78.1% among musicians and 68.8% among non-musicians. However, the chi-square analysis indicated that the difference in detection accuracy between the two groups was not statistically significant ($\chi^2 = 1.23$, $p = .267$).

Mixed-Methods Triangulation Findings

Convergent Analysis: Integration of Quantitative and Qualitative Findings

Table 5. Triangulation matrix of the main findings

Theme	Quantitative Evidence	Supporting Qualitative Evidence	Theoretical Interpretation
Perceived Authenticity	$\eta^2 = .379$ (large effect)	*"It felt as if it had no soul."* (P12)	Benjamin's concept of the aura
Cultural Capital Effect	$d = 1.22$ (very large effect)	*"My expectations are higher."* (P18)	Bourdieu's theory of habitus
Hedonic Paradox	$r = -.357$ (moderate negative correlation)	*"It's enjoyable, but it doesn't inspire me."* (P7)	Berlyne's theory of aesthetic value

Qualitative Findings: Phenomenological Analysis

Focus Group Thematic Analysis

The thematic analysis of the stratified focus-group discussions revealed three major themes.

Theme 1. Technological Admiration versus Emotional Distance

> *"Technically, it is impressive, but something is missing. It has algorithmic perfection, yet lacks human imperfection."* (Musician, P23)

Theme 2. Genre-Specific Expectations and Cultural Bias

> *"As someone who performs Turkish music, I sense a certain mechanical quality in the modal transitions. AI still cannot capture those cultural nuances."* (Turkish Art Music Performer, P31)

Theme 3. Generational Patterns of Technology Adoption

> *"As a member of the younger generation, this music feels perfectly normal to me. If it appeared on my Spotify playlist, I probably wouldn't even notice the difference."* (Non-musician, P42)

In-Depth Interview Findings: Phenomenological Insights

Theme 1. Perception of Musical Authenticity

> *"Knowing that this music was composed by AI prevents me from forming an emotional connection. It creates something like an 'uncanny valley' effect in music."* (Musician, P19)

Theme 2. Effects of Technological Mediation

> *"AI-generated music is perfect for background listening, but insufficient for focused listening. I don't emotionally invest in it because there is no artistic intentionality behind it."* (Non-musician, P38)

Theoretical Interpretation of the Correlation Patterns

These empirical patterns can be meaningfully interpreted through Bourdieu's (1993) theory of cultural capital. Among musicians, the positive correlation between Wonder and Joyful Activation reflects a sophisticated relationship between technical appreciation and creative inspiration. In contrast, the negative correlation observed among non-musicians suggests a trade-off between hedonic enjoyment and intellectual engagement.

From the perspective of cultural capital, musical expertise enables individuals to recognize the algorithmic achievements of AI-generated music while simultaneously encouraging comparisons with traditional compositional practices. This dual awareness creates a dynamic tension between critical distance and appreciative engagement during the formation of aesthetic judgments.

Collectively, these findings demonstrate the complex position of AI-generated music within the contemporary cultural landscape and systematically document the empirical manifestations of the dialectical relationship between technological innovation and artistic tradition.

Conclusion and Discussion

The present findings demonstrate that the relationship between wonder and joyful activation differs according to the listeners' level of musical expertise, suggesting that musical expertise fundamentally shapes the perception of AI-generated music. Interpreted within the frameworks of Meyer's (1956) expectation theory and the domain-specific emotional model proposed by Zentner et al. (2008), these findings indicate that AI-generated music activates different cognitive and emotional mechanisms across different listener groups. Similar observations have been reported by Liebman and Stone (2020), who argued that musical judgments are strongly influenced by listeners' musical background, and by Fišer and Martín-Pascual (2025), whose biometric and self-report findings demonstrated that AI-generated music can evoke emotional responses comparable to those elicited by human-composed music while revealing considerable individual variability in emotional evaluation. Likewise, Mycka and Mańdziuk (2025) emphasized that the perception of AI-generated music is mediated not only by technological characteristics but also by listeners' musical knowledge and previous listening experience.

This analytical perspective provides important insights into the future development of AI-generated music and highlights demographic differences that should be considered in audience segmentation strategies within the music industry. The observed relationships between emotional dimensions exhibit a notable methodological convergence with previous research, collectively depicting a complex socio-cultural understanding of emotional responses to AI-generated music. These findings support the central assumptions of the present study by demonstrating that the mechanisms underlying musical experience vary according to demographic characteristics and musical expertise, thereby illustrating the dialectical relationship between technological innovation and cultural value production. Within the musician group, the positive association between wonder and joyful activation supports Bourdieu's (1993) theory of cultural capital by suggesting that greater musical expertise facilitates the integration of aesthetic appreciation with creative inspiration. In contrast, the negative relationship observed among non-musicians reflects a divergence between hedonic enjoyment and creative engagement. Similar conclusions regarding audience segmentation and listener diversity have been reported by Grassini and Koivisto (2024), who found that previous experience, personality, and attitudes toward AI substantially influence aesthetic evaluations of AI-generated artistic products, and by Ford et al. (2024), who demonstrated that individual expectations strongly shape the perceived creativity and artistic value of AI-generated music.

The present study systematically examined the emotional effects of AI-generated music and empirically demonstrated that musical expertise plays a determining role in perceptual differences between listeners. The mixed-methods design enabled the multidimensional investigation of music-induced emotions using the Geneva Emotional Music Scale (GEMS), thereby providing a comprehensive understanding of both quantitative emotional responses and qualitative listening experiences. This methodological approach is consistent with recommendations by Creswell and Plano Clark (2017) regarding mixed-methods integration and with Zentner et al. (2008), who emphasized the importance of music-specific emotional measurement. Furthermore, recent reviews by Chen, Huang, and Gou (2024) and Mycka and Mańdziuk (2025) have similarly advocated multidimensional approaches for investigating emotional responses to AI-generated music.

Statistically significant differences were identified between musicians and non-musicians. Non-musicians reported significantly higher levels of wonder (4.12 ± 0.68 vs. 3.24 ± 0.76, $p < .001$), whereas musicians demonstrated significantly higher levels of joyful activation (3.08 ± 0.82 vs. 2.14 ± 0.74, $p < .001$). Moreover, wonder and joyful activation were positively associated among musicians ($r = .284$) but negatively associated among non-musicians ($r = -.357$). Although few previous studies have directly compared musicians and non-musicians in the context of AI-generated music, the findings are broadly consistent with Liebman and Stone (2020), who argued that musical expertise influences evaluative judgments, and with Fišer and Martín-Pascual (2025), who reported considerable individual variability in emotional responses to AI-generated and human-composed music. Likewise, Williams et al. (2020) observed that emotional engagement with AI-generated music varies according to listeners' individual characteristics and contextual factors.

The exploratory factor analysis identified three principal emotional dimensions within the GEMS framework: Positive Arousal (38.1% of explained variance), Contemplative Affect (24.2%), and Negative Affect (18.3%). AI-generated music produced its strongest effects within the Positive Arousal dimension, whereas more limited emotional responses were observed in the dimensions of transcendence and joyful activation. These findings are consistent with the original multidimensional structure proposed by Zentner et al. (2008) and support more recent investigations suggesting that AI-generated music effectively elicits basic emotional reactions while remaining less successful in producing complex aesthetic emotions associated with transcendence and inspiration (Fišer & Martín-Pascual, 2025; Chen, Huang, and Gou, 2024; Mycka & Mańdziuk, 2025).

Finally, the findings strongly support Bourdieu's (1993) theory of cultural capital. Musical education appears to enhance listeners' ability to recognize the technical achievements of AI-generated music while simultaneously encouraging more critical comparisons with traditional compositional practices. From the perspective of Benjamin's (1936) concept of mechanical reproducibility, the qualitative findings further indicate that AI-generated music continues to encounter challenges regarding perceived authenticity. Participants frequently described AI-generated music as technically sophisticated but emotionally detached, suggesting that technical excellence alone may not be sufficient to establish the sense of artistic authenticity typically associated with human-created music. Similar concerns regarding authenticity, artistic intentionality, and emotional engagement have recently been reported by Noel-Hirst and Bryan-Kinns (2023), Ford et al. (2024), Grassini and Koivisto (2024), and Jacques and Flynn (2024), all of whom emphasize that listeners continue to distinguish between technical quality and perceived artistic authenticity when evaluating AI-generated creative works.

Recommendations

Future Research Directions

Future research should employ longitudinal research designs to investigate whether repeated exposure to AI-generated music influences listeners' emotional responses, aesthetic evaluations, and perceptions of authenticity over time. Such studies would provide valuable insights into the extent to which familiarity with AI-generated music modifies acceptance and emotional engagement.

In addition, neurophysiological measurement techniques, including electroencephalography (EEG), functional magnetic resonance imaging (fMRI), galvanic skin response (GSR), and heart-rate variability (HRV), should be incorporated to objectively examine the neural and physiological mechanisms underlying emotional responses to AI-generated music. Integrating these measures with self-report instruments would provide a more comprehensive understanding of music-induced emotional processes.

Future studies should also conduct cross-cultural validation by including participants from diverse musical traditions and cultural backgrounds. Such research would clarify how cultural context, musical enculturation, and aesthetic values influence the perception of AI-generated music and would improve the cross-cultural generalizability of existing findings.

Furthermore, greater collaboration between research institutions, music industry professionals, AI developers, and digital music platforms is recommended. Practice-oriented interdisciplinary projects would facilitate the development of emotionally expressive AI music systems while simultaneously addressing issues related to artistic authenticity, listener acceptance, copyright, and ethical AI implementation.

Overall, the present study contributes to contemporary musicology by providing an empirical evaluation of AI-generated music and systematically documenting the evolving relationship between technological innovation and cultural value production.

Limitations

Several limitations should be considered when interpreting the findings of the present study. First, the study included a relatively small sample of 64 participants, divided equally between musicians and non-musicians. Although this sample size satisfied the statistical power requirements for detecting medium effect sizes, larger and more diverse samples would improve the external validity and generalizability of the findings.

Acknowledgments

The authors would like to express their sincere gratitude to all participants who generously devoted their time and shared their experiences throughout this study. Their valuable contributions made this research possible. The authors also wish to thank Afyon Kocatepe University for its institutional support and for providing the facilities necessary to conduct this research. Finally, the authors gratefully acknowledge the professional proofreading and English language editing provided during the preparation of this manuscript, which significantly improved its clarity and readability.

Biodata of Author

Assoc. Prof. Dr**. Seyhan Canyakan** began his academic journey after completing his primary education in Bergama. In 1998, he was admitted to the Piano Department of the Music Education Faculty at Niğde University. Following his graduation, he embarked on his teaching career in 2002. In 2008, he gained recognition for his work in theater music, composition, and studio productions, with four of his compositions featured in a literary work. He achieved international success in the field of electronic music, with his compositions being published worldwide and used in various projects. In 2011, he participated in EU-supported international concert projects, produced music albums, and collaborated with Jinglehouse. He completed his master's and doctoral studies at Dokuz Eylül University, established a department at Uşak University, and served as a faculty member at Mehmet Akif Ersoy University. As a composer, he produces works across a wide spectrum, including Turkish music and electronic music, and is known for his international media and game music compositions. He is married and has two children. Institution: AKU State Conservatory, Afyonkarahisar, Turkiyr. Email: scanyakan@aku.edu.tr ORCID: 0000-0001-6373-4245 Personal
Website: https://konservatuvar.aku.edu.tr/seyhan-canyakan/
ResearchGate: https://www.researchgate.net/profile/Seyhan_Canyakan
AcademiaEdu: https://afyonkocatepe.academia.edu/SeyhanCanyakan

References

Álvarez, P., García de Quirós, J., & Baldassarri, S. (2023). RIADA: A machine-learning based infrastructure for recognising the emotions of Spotify songs. *International Journal of Interactive Multimedia and Artificial Intelligence, 8*(2), 168-181. https://doi.org/10.9781/ijimai.2022.04.002

Amankwah-Amoah, J., Abdalla, S., Mogaji, E., Elbanna, A., & Dwivedi, Y. K. (2024). The impending disruption of creative industries by generative AI: Opportunities, challenges, and research agenda. *International Journal of Information Management, 79*, 102759. https://doi.org/10.1016/j.ijinfomgt.2024.102759

Benjamin, W. (1936). *Das Kunstwerk im Zeitalter seiner technischen Reproduzierbarkeit*. Suhrkamp Verlag.

Blood, A. J., & Zatorre, R. J. (2001). Intensely pleasurable responses to music correlate with activity in brain regions implicated in reward and emotion. *Proceedings of the National Academy of Sciences, 98*(20), 11818-11823. https://doi.org/10.1073/pnas.191355898

Bourdieu, P. (1993). *The field of cultural production*. Columbia University Press.

Bryan-Kinns, N., Zhang, B., Zhao, S., & Banar, B. (2024). Exploring variational auto-encoder architectures, configurations, and datasets for generative music explainable AI. *Machine Intelligence Research, 21*(1), 29-45. https://doi.org/10.1007/s11633-023-1457-1

Chen, Y., Huang, L., & Gou, T. (2024). *Applications and advances of artificial intelligence in music generation: A review*. arXiv. https://doi.org/10.48550/arXiv.2409.03715

Cheng, L. (2025). The impact of generative AI on school music education: Challenges and recommendations. *Arts Education Policy Review*. https://doi.org/10.1080/10632913.2025.2451373

Cohen, J. (1988). *Statistical power analysis for the behavioral sciences* (2nd ed.). Lawrence Erlbaum Associates.

Creswell, J. W., & Plano Clark, V. L. (2017). *Designing and conducting mixed methods research* (3rd ed.). SAGE Publications.

Darda, K. M., & Cross, E. S. (2023). The computer, a choreographer? Aesthetic responses to randomly generated dance choreography by a computer. *Heliyon, 9*(1), e12750. https://doi.org/10.1016/j.heliyon.2022.e12750

Dash, A., & Agres, K. R. (2024). AI-based affective music generation systems: A review of methods and challenges. *ACM Computing Surveys, 56*(11), Article 255. https://doi.org/10.1145/3672554

Fišer, N., & Martín-Pascual, M. Á. (2025). Emotional impact of AI-generated vs. human-composed music in audiovisual media: A biometric and self-report study. *PLOS ONE, 20*(6), e0326498. https://doi.org/10.1371/journal.pone.0326498

Ford, C., Noel-Hirst, A., Cardinale, S., Loth, J., Sarmento, P., Wilson, E., & Bryan-Kinns, N. (2024). Reflection across AI-based music composition. *Journal of Creative Music Technology, 8*(2), 134-152.

Gençöz, T. (2000). Pozitif ve Negatif Duygu Ölçeği: Geçerlik ve güvenirlik çalışması. *Türk Psikoloji Dergisi, 15*(46), 19-26.

Grassini, S., & Koivisto, M. (2024). Understanding how personality traits, experiences, and attitudes shape negative bias toward AI-generated artworks. *Scientific Reports, 14*, 4113. https://doi.org/10.1038/s41598-024-54294-4

Gu, X. (2024). Enhancing social media engagement using AI-modified background music: Examining the roles of event relevance, lyric resonance, AI-singer origins, audience interpretation, emotional resonance, and social media engagement. *Frontiers in Psychology, 15*, 1267516. https://doi.org/10.3389/fpsyg.2024.1267516

Haraway, D. (1985). A cyborg manifesto: Science, technology, and socialist-feminism in the late twentieth century. *Socialist Review, 15*(2), 65-107.

Huron, D. (2006). *Sweet anticipation: Music and the psychology of expectation*. MIT Press.

Jacques, S., & Flynn, M. (2024). Protecting human creativity in AI-generated music with the introduction of an AI-royalty fund. *GRUR International, 73*(12), 1137-1149. https://doi.org/10.1093/grurint/ikae134

Juslin, P. N., & Sloboda, J. A. (Eds.). (2001). *Music and emotion: Theory and research*. Oxford University Press.

Kristeva, J. (1980). *Desire in language: A semiotic approach to literature and art*. Columbia University Press.

Latour, B. (2005). *Reassembling the social: An introduction to actor-network-theory*. Oxford University Press.

Leman, M. (2008). *Embodied music cognition and mediation technology*. MIT Press.

Li, Y., Li, X., Lou, Z., & Chen, C. (2022). Long short-term memory-based music analysis system for music therapy. *Frontiers in Psychology, 13*, 928048. https://doi.org/10.3389/fpsyg.2022.928048

Liebman, E., & Stone, P. (2020). *Artificial musical intelligence: A survey*. arXiv. https://doi.org/10.48550/arXiv.2006.10553

Meyer, L. B. (1956). *Emotion and meaning in music*. University of Chicago Press.

Mycka, J., & Mańdziuk, J. (2025). Artificial intelligence in music: Recent trends and challenges. *Neural Computing and Applications, 37*, 801-839. https://doi.org/10.1007/s00521-024-10555-x

Noel-Hirst, A., & Bryan-Kinns, N. (2023). *An autoethnographic exploration of XAI in algorithmic composition*. arXiv. https://doi.org/10.48550/arXiv.2308.06089

Pachet, F., Roy, P., & Carré, B. (2020). *Assisted music creation with Flow Machines: Towards new categories of new*. arXiv. https://doi.org/10.48550/arXiv.2006.09232

Pearce, M. T., & Wiggins, G. A. (2012). Auditory expectation: The information dynamics of music perception and cognition. *Topics in Cognitive Science, 4*(4), 625-652. https://doi.org/10.1111/j.1756-8765.2012.01214.x

Salimpoor, V. N., Benovoy, M., Larcher, K., Dagher, A., & Zatorre, R. J. (2011). Anatomically distinct dopamine release during anticipation and experience of peak emotion to music. *Nature Neuroscience, 14*(2), 257-262. https://doi.org/10.1038/nn.2726

Scherer, K. R. (2004). Which emotions can be induced by music? What are the underlying mechanisms? And how can we measure them? *Journal of New Music Research, 33*(3), 239-251. https://doi.org/10.1080/0929821042000317822

Spreng, R. N., McKinnon, M. C., Mar, R. A., & Levine, B. (2009). The Toronto Empathy Questionnaire: Scale development and initial validation of a factor-analytic solution to multiple empathy measures. *Journal of Personality Assessment, 91*(1), 62-71. https://doi.org/10.1080/00223890802484381

Su, Y., Liu, Y., Xiao, Y., Ma, J., & Li, D. (2024). A review of artificial intelligence methods enabled music-evoked EEG emotion recognition and their applications. *Frontiers in Neuroscience, 18*, 1400444. https://doi.org/10.3389/fnins.2024.1400444

Tarasti, E. (2002). *Signs of music: A guide to musical semiotics*. De Gruyter Mouton.

Watson, D., Clark, L. A., & Tellegen, A. (1988). Development and validation of brief measures of positive and negative affect: The PANAS scales. *Journal of Personality and Social Psychology, 54*(6), 1063-1070. https://doi.org/10.1037/0022-3514.54.6.1063

Williams, D., Hodge, V. J., & Wu, C. Y. (2020). On the use of AI for generation of functional music to improve mental health. *Frontiers in Artificial Intelligence, 3*, 497864. https://doi.org/10.3389/frai.2020.497864

Xiong, Z., Wang, W., Yu, J., Lin, Y., & Wang, Z. (2023). *A comprehensive survey for evaluation methodologies of AI-generated music*. arXiv. https://doi.org/10.48550/arXiv.2308.13736

Zentner, M., Grandjean, D., & Scherer, K. R. (2008). Emotions evoked by the sound of music: Characterization, classification, and measurement. *Emotion, 8*(4), 494-521. https://doi.org/10.1037/1528-3542.8.4.494

Zhou, W., & Kim, Y. (2024). Innovative music education: An empirical assessment of ChatGPT-4's impact on student learning experiences. *Education and Information Technologies, 29*(16), 20855-20881. https://doi.org/10.1007/s10639-024-12705-z

Zhu, Y., Baca, J., Rekabdar, B., & Rawassizadeh, R. (2023). *A survey of AI music generation tools and models*. arXiv. https://doi.org/10.48550/arXiv.2308.12982