



Does the listener care? Emotional resonance and connection in the age of algorithmic music

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ABSTRACT

As generative Artificial Intelligence (AI) models achieve high fidelity in mimicking musical structures and timbres, debates surrounding the role of human agency in listener engagement emerge. As the music industry moves to algorithmic music to ensure efficiency, it is not yet clear whether audiences are appreciating music as an independent sonic entity or as a communicative gesture of human will. This paper examined how perceived authorship affects emotional resonance in Kenyan university students through a mixed-methods explanatory sequential design. The study, anchored in the Theory of *Ngoma*, which views music as a complete social institution that needs vital force (*Roho*), questions the belief that acoustic perfection is synonymous with artistic value. A quantitative deceptive listening experiment ($N = 76$) was conducted across student populations drawn from Kabarak University, Kenyatta University, and the Technical University of Kenya. The qualitative phase employed expert elicitation, in which the insights of an international panel of musicologists, AI experts, and cultural theorists were sought. This professional discussion was employed to address the authenticity loss and to interpret the statistical declines in emotional attachment within the framework of African musicology, formalist aesthetics, and neoliberal commodification. The findings showed that explicit knowledge of AI authorship led to a directional decline in listener emotional resonance, even where the tracks were sonically indistinguishable. This suggests a fundamental audience preference for the human spirit and intentionality behind the sound. Consequently, these findings provide critical insights into the limitations of AI in replicating the functional, socio-spiritual, and communal dimensions of African musical arts.

Keywords: AI Music, Algorithmic Music, Authenticity, Emotional Resonance, Music Perception, and *Ngoma* Theory.

INTRODUCTION

The rapid growth of Generative Artificial Intelligence (AI) is causing a seismic shift in the global music industry. Deep learning and neural audio synthesis technologies like the Suno and Udio platforms have progressed to produce high-quality, complex algorithmic music that competes with human music in genre, timbre, and form. Deep learning systems, such as Generative Adversarial Networks (GANs) and transformer models, now process large amounts of data to detect patterns, enabling them to recreate

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human creativity and produce a wide range of results, such as scores or even full audio songs.¹ It is the first time in history that the technical barrier to music creation has been successfully broken, and users are now able to create high-quality audio based on the simplest textual prompt. This technological innovation democratises the production of music by allowing people without any background in music to create songs easily, thus changing how music is composed, produced, and consumed.² This democratisation of production challenges the traditional definition of the musician and raises profound questions about the future of creativity in an age of automated art. With these tools becoming more ubiquitous, the industry will experience a future where the line between human-composed and machine-generated art cannot be heard anymore, which will necessitate a reassessment of authorship itself.³ This emergence of algorithmic creativity essentially challenges the accepted notions of originality, requiring a theoretical analysis of creativity in terms of human-computer collaboration and distributed agency.

However, this technological advancement has triggered an ontological crisis on the value of music. While AI models can replicate the phenomenology of music, the precise arrangement of frequencies, rhythms, and harmonies, they inherently lack the lived experience that typically informs human composition. The music industry has traditionally been driven by a belief that audiences are being offered an audio product, but this ideology overlooks the fact that listeners may appreciate the process, the human struggle, purpose, and story behind the sound. Empirical research points to the fact that, although AI systems can reproduce stylistic probabilities and musical structures, they cannot recreate the emotional intentionality and cultural context on which human musical meaning is based. This tends to create pieces that are technically correct but appear to be emotionally detached.⁴

This deficit highlights a critical tension: whether the listener values the song for its sonic beauty or for the human soul they believe resides within it. Philosophically, music is viewed not merely as a sonic object but as a form of fully embodied human experience and agency, suggesting that AI-generated content poses a threat to the essential communicative bond between artist and audience.⁵ When the human component is indispensable, then algorithmic music can be described as a mere hollow shell, a simulation of emotion with no essential emotional source that runs the risk of draining the unique features that make up authentic artistic expression.⁶

Psychologically, this tension is often explained through a heuristic, where consumers value an object more when they perceive that significant human labour went into its creation. This is applicable to music, where the emotional effect of a composition can be determined by whether the listener believes in a human actor. If a listener discovers that a deeply moving ballad was generated in seconds by an algorithm, the parasocial connection, the illusion of intimacy with the artist, may collapse. This phenomenon, often described as an authenticity deficit, implies that the caring described in this study is not merely a preference but a fundamental psychological requirement for deep emotional engagement. Studies further indicate that since AI compositions are created based on statistical trends instead of experience, they do not possess the expressive purpose needed to convey an emotional touch, which can often make them appear soulless or mechanically one-dimensional to listeners.⁷ Consequently, empirical studies indicate that listeners report significantly lower emotional intensity and preference when they

¹ Yongxin Zhou, Yuhui Wang, and Jiayu Su, "A Study on Factors Influencing Music Enthusiast's Behavioral Intention to Use Generative AI for Music Composition Based on an Expanded Technology Acceptance Model," *Scientific Reports* 15, no. 1 (December 29, 2025): 44802, <https://doi.org/10.1038/s41598-025-28532-2>.

² Suqi Chia, Andree Hartanto, and Eddie M.W. Tong, "Do Listeners Devalue AI-Generated Pop Music? Exploring Negative Biases in Listeners' Responses to AI-Labelled vs Human-Labelled Pop Music," *Computers in Human Behavior: Artificial Humans* 6 (December 2025): 100217, <https://doi.org/10.1016/j.chbah.2025.100217>.

³ Kimaya Lecamwasam and Tishya Ray Chaudhuri, "Exploring Listeners' Perceptions of AI-Generated and Human-Composed Music for Functional Emotional Applications," *ArXiv Preprint ArXiv:2506.02856*, 2025.

⁴ Ismail Eraslan, "Artificial Intelligence and the Rewriting of Musical Memory: A Cognitive Perspective," *Science Development* 6, no. 3 (July 28, 2025): 114–20, <https://doi.org/10.11648/j.scidev.20250603.18>.

⁵ Casey Haskins, "Is AI a Threat to Human Music? (A Neo-Deweyan Perspective)," *The Journal of Aesthetics and Art Criticism* 83, no. 3 (September 23, 2025): 238–53, <https://doi.org/10.1093/jaac/kpaf024>.

⁶ Sanjukta Das and Rituparna Kundu, "The Ethics of Artificial Intelligence in Creative Arts: A Comprehensive Review," *Interdisciplinary International Journal of Advances in Social Sciences, Arts and Humanities* 01, no. 01 (2024): 27–34, <https://doi.org/10.62674/ijassah.2024.v1i1.003>.

⁷ Chia, Hartanto, and Tong, "Do Listeners Devalue AI-Generated Pop Music? Exploring Negative Biases in Listeners' Responses to AI-Labelled vs Human-Labelled Pop Music."

believe a piece of music is AI-generated, regardless of its actual acoustic quality, as the perception of human authorship is intrinsic to the assignment of value.⁸ This anthropomorphic bias highlights that listeners inherently associate meaningful, complex composition with human agency; when that agency is absent, the communicative bond is severed, and the music is relegated to a lower status. The listener is not just hearing a melody; they are participating in a communicative act with another consciousness, a connection that algorithms cannot currently reciprocate.

Despite the urgency of this issue, existing literature has largely focused on Western populations and aesthetic frameworks, often reducing the debate to a ‘Turing Test’ of whether listeners can distinguish humans from AI audio.⁹ This strategy is inadequate in African settings, where music is not commonly considered an independent sound phenomenon but rather a practical instrument of societal unity and spiritual expression.¹⁰ Music in Kenya, for instance, functions within the paradigm of Ngoma, a holistic institution of sound that is intrinsically connected to movement, community engagement, and spiritual purpose. Music is a crucial means of communication between the living and the supernatural worlds.¹¹ Western research does not cover the interaction of AI with this functional perception, where the agency of the musician is the key to the healing and bonding process. This means, therefore, that the implementation of AI technologies based on Western data models in relation to indigenous heritage can lead to the further development of a new form of digital colonialism,¹² which is expressed in the decontextualisation of divine rituals and the violation of data sovereignty. An AI may generate the sonic texture of Ngoma, but it lacks the African communal ethos, the participatory and socially embedded nature of creativity required to perform its function effectively. To address this epistemological gap, this study argues that despite the acoustic indistinguishability of AI-generated music, it suffers from a fundamental authenticity deficit that severs the communicative bond between artist and listener; furthermore, when viewed through the Kenyan paradigm of Ngoma, algorithmic music creates a profound cultural dissonance by simulating the sonic texture of ritual without the indispensable human agency, communal ethos, and spiritual intent.

LITERATURE REVIEW

Algorithmic Capability and the Musical Turing Test

The rapid advancement of generative AI, particularly through deep learning models such as Generative Adversarial Networks (GANs) and transformer architectures, has effectively closed the acoustic gap between human and machine composition.¹³ Initial empirical studies were mostly devoted to the Musical Turing Test, exploring listeners’ ability to differentiate between human and AI-generated sound.¹⁴ Recent experiments with both symbolic music and high-fidelity sound show that listeners always score near-chance levels in blind discrimination experiments in the case of random human versus algorithmic music. This is further supported by modern industry surveys, which show that during blind listening tests, most listeners (97%) cannot fully identify AI-generated tracks.¹⁵ Nevertheless, a significant divergence in the reception is revealed as soon as the technological origin is revealed to the audience.¹⁶ Despite their inability to hear the difference, 52% of surveyed listeners report feeling uncomfortable

⁸ David Stammer, Hannah Strauss, and Peter Knees, “Perception of AI-Generated Music--The Role of Composer Identity, Personality Traits, Music Preferences, and Perceived Humanness,” *ArXiv Preprint ArXiv:2512.02785*, 2025.

⁹ A. M. Turing, “I.—Computing Machinery and Intelligence,” *Mind* LIX, no. 236 (October 1, 1950): 433–60, <https://doi.org/10.1093/mind/LIX.236.433>.

¹⁰ Amon Kipyegon Kirui, Mellitus N. Wanyama, and Madimabe Geoff Mapaya, “Epistemics of African Music Performance: Navigating Knowledge, Tradition, and the Digital Frontier,” *African Musicology Online* 14, no. 2 (June 24, 2025): 14–24, <https://doi.org/10.58721/amo.v14i2.1107>.

¹¹ Nureni Aremu Bakenne and Israel A Fadipe, “Extra-Mundane Communication in Ayinla Omowura’s Music: Exploring Connections Between a Tool and an Agent,” in *Indigenous African Popular Music, Volume 2: Social Crusades and the Future* (Springer, 2022), 3–29.

¹² Kirui, Wanyama, and Mapaya, “Epistemics of African Music Performance: Navigating Knowledge, Tradition, and the Digital Frontier.”

¹³ Zhou, Wang, and Su, “A Study on Factors Influencing Music Enthusiast’s Behavioral Intention to Use Generative AI for Music Composition Based on an Expanded Technology Acceptance Model.”

¹⁴ Flavio Figueiredo et al., “Echoes of Humanity: Exploring the Perceived Humanness of AI Music,” *ArXiv Preprint ArXiv:2509.25601*, 2025.

¹⁵ Deezer and Ipsos, *Industry Survey Finds Most Listeners Cannot Tell AI Music from Human Work* (Darwin Beats, 2025).

¹⁶ Soundverse, “The Authenticity Gap: Human Perception and the Aesthetic Valuation of AI-Generated Music,” 2025.

with this lack of distinguishability, and 80% demand clear labelling for AI-generated music.¹⁷ This paradox suggests that the aesthetic valuation of music is not merely an objective response to acoustic features, but a socially constructed judgement heavily influenced by the perceived identity and authenticity of the composer.¹⁸

The Effort Heuristic and Parasocial Connection

To understand this bias against algorithmic music, scholars frequently point to the ‘effort heuristic’ proposed by Kruger et al.¹⁹ The effort heuristic posits that individuals intuitively assess the quality and value of an artefact based on the perceived magnitude of labour required to produce it. In the context of the creative arts, works believed to be the result of intense human struggle and deliberate technical investment are afforded a higher aesthetic value than those generated instantaneously by automation.²⁰ Moreover, the actual nature of modern music consumption is based on Parasocial Interaction (PSI), a one-sided emotional connection between a listener and an artist.²¹ Empathy is a vital element of PSI; listeners relate to a song by picturing the ghost in the machine, a feeling person who truly felt the heartbreak or the strength being expressed.²² The absence of this lived experience in AI-generated music creates a ‘parasocial void,’ alienating listeners who seek genuine human connection rather than mere sonic stimulation.²³ This phenomenon closely aligns with recent psychological findings regarding artificial personas, demonstrating that virtual influencers suffer from a severe ‘authenticity deficit’ because they are devoid of authentic emotions and relatable life experiences.²⁴

Ngoma and African Musical Arts

Recent work has begun to sketch what a culturally attuned engagement with AI might require, namely, ethical community engagement, co-design, and culturally informed data collection,²⁵ but empirical listener studies from within the Ngoma paradigm remain rare. This reductionist attitude is essentially inconsistent with the African epistemology, namely, the notion of *Ngoma* holism.²⁶ According to fundamental theorists like Nketia and Nzewi, African musical arts are not only characterized by their acoustic form but also by their irreducible combination of sound, dance, community engagement, and social role.²⁷ In this paradigm, as argued by Yende, music is an ontological practice with strong roots in social structures, historical consciousness, and spiritual beliefs.²⁸ The traditional musician acts as a vital conduit for communal memory and spiritual force, providing a living dimension that authenticates the performance. Thus, a considerable lack of studies using this functionalist framework on generative AI still exists. While Western studies primarily ask if AI sounds ‘real’ or technically proficient, they

¹⁷ Deezer and Ipsos, *Industry Survey Finds Most Listeners Cannot Tell AI Music from Human Work*.

¹⁸ Soundverse, “The Authenticity Gap: Human Perception and the Aesthetic Valuation of AI-Generated Music.”

¹⁹ Justin Kruger et al., “The Effort Heuristic,” *Journal of Experimental Social Psychology* 40, no. 1 (January 2004): 91–98, [https://doi.org/10.1016/S0022-1031\(03\)00065-9](https://doi.org/10.1016/S0022-1031(03)00065-9).

²⁰ Jennifer Rix et al., “The Algorithm Discount: Explaining Consumers’ Valuation of Human- versus Algorithm-Created Digital Products,” *Journal of Management Information Systems* 42, no. 2 (April 3, 2025): 633–68, <https://doi.org/10.1080/07421222.2025.2487308>.

²¹ Mohd Junaaid Akhtar and Sarita Nagvanshi, “Parasocial Interaction and Virtual Influencers,” in *Redefining the Future of Digital Marketing With Virtual Influencers* (IGI Global, 2025), 151–80, <https://doi.org/10.4018/979-8-3373-0255-3.ch006>.

²² K. Aruwajoye, “Floating Signifiers: AI, Semiotics, and the Crisis of Meaning in Music ” (Dartmouth College, 2025).

²³ Aruwajoye, “Floating Signifiers: AI, Semiotics, and the Crisis of Meaning in Music .”

²⁴ Donia Khalfallah and Veronika Keller, “Authenticity, Ethics, and Transparency in Virtual Influencer Marketing: A Cross-Cultural Analysis of Consumer Trust and Engagement: A Systematic Literature Review,” *Acta Psychologica* 260 (October 2025): 105573, <https://doi.org/10.1016/j.actpsy.2025.105573>.

²⁵ Kirui, Wanyama, and Mapaya, “Epistemics of African Music Performance: Navigating Knowledge, Tradition, and the Digital Frontier.”

²⁶ Jerry Rutsate, “Ngoma Materiality and Instrumentality: Reconfiguring Malawian Indigenous Music Digitization for Global Music Appreciation,” in *De-Neocolonizing Africa* (Cham: Springer Nature Switzerland, 2024), 449–61, https://doi.org/10.1007/978-3-031-66304-8_25.

²⁷ J. H. K. Nketia, *The Music of Africa* (W. W. Norton & Company, 1974); Meki Nzewi, “African Music Creativity and Performance: The Science of the Sound,” *Voices: A World Forum for Music Therapy* 6, no. 1 (March 1, 2006), <https://doi.org/10.15845/voices.v6i1.242>.

²⁸ Sakhiseni Joseph Yende, “Towards a Theory of Indigenosociomusicology: African Perspectives on Indigenous Knowledge, Social Meaning, and Decolonial Music Studies,” *Eastern African Journal of Humanities and Social Sciences* 5, no. 1 (2026): 61–71.

frequently fail to ask if it is ‘spiritually valid’ or communally meaningful.²⁹ This paper bridges this essential epistemological gap by exploring the question of whether the perceived soullessness of AI is reflected in an empirically measurable rejection by Kenyan listeners whose aesthetic values are deeply embedded in the functional *Ngoma* culture.

THEORETICAL FRAMEWORK

This study is theoretically anchored in the *Ngoma* paradigm, a foundational framework derived from Bantu epistemologies that conceptualises musical arts as a holistic social action rather than a passive, autonomous sonic object.³⁰ Contrary to the positive aspects of Western positivist aesthetics, where music is largely judged by such structural components as pitch and harmony, the *Ngoma* paradigm characterises music by the symbiotic fusion of sound, dancing, community engagement, and spirituality.³¹ This theoretical prism rests on three appraisal pillars. To begin with, it highlights total integration, where the musical event is an immersive, multimodal experience and where the drum, song, and dance are one and the same institution.³² Second, it is pegged on functional efficacy; the value of a composition is assessed by its socio-spiritual utility, which becomes what Nzewi calls the science of sound, which has the effect of creating affective energy to heal and unite people.³³ Lastly, the Bantu ontological idea of *Ntu*, or vital force, supports the framework.³⁴ Within this philosophy, *Muntu* designates a human being endowed with intelligence and spirit, whereas *Kintu* refers to inanimate objects devoid of this essence.³⁵ The aesthetic echo of a composition therefore inherently relies on the audience perceiving this human intensity.

The *Ngoma* framework offers a solid analytical approach to the question of the authenticity deficit of algorithmic music among Kenyan audiences. The theory anticipates a method of cultural resistance to generative AI models, e.g., Suno or Udio, based on a deep ontological divide. Although these sophisticated neural networks can perfectly reproduce the acoustic surface and phenomenological aspects of music, they simply do not possess the ontological status that is the necessary property of the *Ngoma* paradigm. An algorithm is fundamentally a *Kintu*, a mere technological tool or thing devoid of ancestral lineage, social identity, and the indispensable “vital force” that authenticates a performance.³⁶ This paper, therefore, hypothesises that among the students at Kabarak, Kenyatta, and the Technical University of Kenya, where aesthetic values are strongly oriented towards music as a human-focused form of communication, fully AI-generated music will create a crisis of connection. Since these listeners subconsciously desire the human intentionality and group spirit that *Ngoma* deems necessary to a complete musical experience, they will tend to find AI-generated music spiritually barren and will eventually reject it not due to its acoustic incompetence, but due to its inherent inhumanity and absence of agency.

METHODOLOGY

The research design in this study was a mixed-methods explanatory sequential design (QUAN → qual) that lies within a pragmatic research paradigm, which favours the combination of different methodological approaches to explain complex sociocultural phenomena.³⁷ This two-way structure was

²⁹ Yende, “Towards a Theory of Indigenosociomusicology: African Perspectives on Indigenous Knowledge, Social Meaning, and Decolonial Music Studies.”

³⁰ Nketia, *The Music of Africa*.

³¹ Yende, “Towards a Theory of Indigenosociomusicology: African Perspectives on Indigenous Knowledge, Social Meaning, and Decolonial Music Studies.”

³² Nketia, *The Music of Africa*.

³³ Nzewi, “African Music Creativity and Performance: The Science of the Sound.”

³⁴ J. Kavusa, “Humans and Non-Humans as *נפש חיה* and *Ntu*-Beings: Ecological Appraisal of Gen 2:7 and 19 in Dialogue with African-Bantu Indigenous Cosmology,” *Old Testament Essays* 35, no. 2 (January 1, 2022): 149, <https://doi.org/10.17159/2312-3621/2022/v35n2a3>.

³⁵ Alexis Kagame, *Sprache Und Sein: Die Ontologie Der Bantu Zentralafrikas* (Kivouvou, Ed. Bantoues, 1985); Kavusa, “Humans and Non-Humans as *נפש חיה* and *Ntu*-Beings: Ecological Appraisal of Gen 2:7 and 19 in Dialogue with African-Bantu Indigenous Cosmology.”

³⁶ Kavusa, “Humans and Non-Humans as *נפש חיה* and *Ntu*-Beings: Ecological Appraisal of Gen 2:7 and 19 in Dialogue with African-Bantu Indigenous Cosmology.”

³⁷ John W Creswell and Vicki L Plano Clark, *Designing and Conducting Mixed Methods Research* (Sage publications, 2017).

ideally positioned to examine the issue of authenticity deficit in algorithmic music. The first quantitative stage was conducted in a postpositivist paradigm, where a controlled experimental design was used to objectively isolate and quantify the extent of bias against AI-generated music. However, recognising that statistical variances cannot sufficiently elucidate the underlying epistemological or ontological conflicts, particularly within the African functionalist framework of *Ngoma*, the study seamlessly transitioned into a constructivist qualitative phase.³⁸ Consequently, the broad statistical trends and expectancy violations established in the primary phase directly informed the purposeful sampling and thematic trajectory of the subsequent expert-elicitation phase. The target population comprised undergraduate university students in Kenya. To avoid the ecological fallacy of conflating institutional ethos with individual aesthetic worldviews, the study treated the participants from Kabarak University, Kenyatta University, and the Technical University of Kenya as a single, unified demographic pool. Collecting data across these three geographically and institutionally distinct campuses ensured a robust and diverse cross-section of student perspectives.

The sampling procedure was operationalised in two distinct phases:

Phase 1 (Quantitative Strand)

A purposive, cross-sectional sample of 76 participants ($N = 76$) was used in the quantitative phase. This was a sufficient sample size to test the main and interaction effects in the 2×2 factorial research design. To control for baseline differences in musical and technical literacy, the sample included representation across distinct academic disciplines (Arts/Humanities and STEM/Business). To measure individual aesthetic values in a more organic way, the survey instrument included baseline covariates, such as the self-reported significance of the human background of an artist, before the experimental exposure.

Phase 2 (Qualitative Strand)

Recognising that undergraduate listeners, while capable of reporting their aesthetic preferences, may lack the theoretical vocabulary to articulate the underlying ontological shifts, the qualitative phase employed a digital ethnography of scholarly discourse. This methodological choice was deliberate: the explanatory sequential design required the qualitative strand to explain *why* the quantitative pattern emerged, and expert theorists were better positioned than lay listeners to articulate the ontological and cultural mechanisms behind the observed authenticity gap. To achieve the explanatory role of the mixed-methods design, qualitative information was elicited through an open-source dialogue between experts and subjected to thematic analysis. A structured and publicly available academic forum (ResearchGate) was systematically reviewed, in which an international panel of experts (musicologists, AI researchers, and cultural theorists) discussed the topic. This panel offered high-level theoretical explanations, drawing on Hanslickian formalism and Crossian communicative theories, the Southern African ‘DJ phenomenon,’ and neoliberal commodification, to put the quantitative matrices produced by the student cohort into perspective. Coding proceeded in two passes. First, deductive codes were derived a priori from the *Ngoma* framework (*Muntu*, *Roho*, *Kintu*, functional efficacy). Second, inductive open codes were generated from the expert discourse using a hybrid thematic analysis approach.³⁹ Two rounds of coding were undertaken, with discrepancies resolved through iterative review; where the ATLAS.ti LLM-assisted analysis diverged from manual coding, the manual reading was retained. Trustworthiness was addressed through credibility (triangulation of expert voices), transferability (thick description of context), dependability (audit trail of coding decisions), and confirmability (reflexive memos maintained throughout the process).

Eligibility Criteria

To ensure the internal validity of the experimental design and to guarantee that the sample was representative of the target population, a set of strict eligibility criteria was created. Data screening was

³⁸ Michael D. Fetters, Leslie A. Curry, and John W. Creswell, “Achieving Integration in Mixed Methods Designs—Principles and Practices,” *Health Services Research* 48, no. 6pt2 (December 23, 2013): 2134–56, <https://doi.org/10.1111/1475-6773.12117>.

³⁹ Virginia Braun and Victoria Clarke, “Using Thematic Analysis in Psychology,” *Qualitative Research in Psychology* 3, no. 2 (2006): 77–101.

carried out to remove confounding variables associated with auditory processing, demographic misalignment, or data attrition. The inclusion and exclusion parameters are detailed in **Table 1**.

Table 1: Participant Inclusion and Exclusion Criteria

Criterion type	Parameter	Rationale
Inclusion	Active undergraduate enrolment at Kabarak, Kenyatta, or the Technical University of Kenya.	Ensures demographic consistency and maintains the boundaries of the unified sampling frame.
Inclusion	Self-reported normal auditory processing capabilities.	Fundamental prerequisite for participating in a high-fidelity musical listening experiment and accurately perceiving acoustic timbres.
Inclusion	Provision of explicit, written informed consent.	Mandated by institutional ethics review boards (IRBs) for human-subject research involving experimental deception.
Inclusion	Complete submission of the Phase 1 listening task and GEMS-9 evaluation.	Prevents missing-data artefacts, ensuring complete datasets for the Two-Way ANOVA.
Exclusion	Postgraduate students, alumni, faculty, or unaffiliated individuals.	Prevents age and educational stratification from acting as confounding variables in aesthetic judgements.
Exclusion	Self-reported hearing impairments or inability to use standard audio equipment.	Mitigates the risk of physiological limitations skewing the affective evaluation of the sonic stimuli.
Exclusion	Incomplete survey responses or failure to pass embedded attention checks.	Safeguards the dataset against inattentive responding, preserving the statistical integrity of the quantitative phase.

Experimental Design and Instrumentation

To isolate cognitive bias and acoustic preference rigorously, a 2×2 factorial experimental design (randomised) was used in the quantitative phase. The independent variables were Actual Origin (Human vs. AI) and Labelled Origin (“Human” vs. “AI”). To remove acoustic confounding variables, participants rated four 45-second musical passages that were well matched in genre (cinematic/ambient), tempo, dynamic range, and overall production fidelity. Drawing on established cognitive-bias methodologies,⁴⁰ the experiment employed a deception protocol to test for expectancy violations. The stimulus presentation was divided into two conditions:

i. Congruent condition

Human-composed tracks were accurately labelled “Human,” and AI-generated tracks were labelled “AI.”

ii. Incongruent condition (deception)

Labels were inverted; human tracks were presented as “AI,” and AI tracks were presented as “Human.”

The dependent variable, emotional resonance, was measured using the Geneva Emotional Music Scale (GEMS-9). GEMS-9 was chosen intentionally as an alternative to traditional affective circumplex models based on its strong psychometric validation of complex, music-specific aesthetic feelings

⁴⁰ Stammer, Strauss, and Knees, “Perception of AI-Generated Music--The Role of Composer Identity, Personality Traits, Music Preferences, and Perceived Humanness”; Dimiter Zlatkov, Jeff Ens, and Philippe Pasquier, “Searching for Human Bias Against AI-Composed Music,” 2023, 308–23, https://doi.org/10.1007/978-3-031-29956-8_20.

(wonder, nostalgia, transcendence) that correspond closely to the multidimensional experience of *Ngoma*.⁴¹

Data Analysis

The analytical framework integrated computational rigour with deep thematic synthesis.

Quantitative Analysis

Data processing and statistical modelling were executed using the Python programming language to ensure high computational transparency and reproducibility. After systematic data cleaning with the Pandas library, assumption checks were carried out. Normality of the residuals was assessed with the Shapiro–Wilk test, and homogeneity of variance across the four track conditions was assessed with Levene’s test (centred on the median). Where assumptions were partially violated, results were interpreted with appropriate caution, and non-parametric checks were consulted as a robustness measure. A Two-Way Analysis of Variance (ANOVA) was then calculated with the help of SciPy and Statsmodels. This evaluated both the main effects and the critical interaction effect between the actual origin of the music and its perceived origin on GEMS-9 scores. Effect sizes were reported as partial eta squared (η^2_p), with 95% confidence intervals computed for each condition mean; post-hoc pairwise contrasts were examined using Tukey’s HSD, and Cohen’s *d* was reported for each pair to quantify the magnitude of any observed difference.

The Qualitative Analysis

The extracted expert discourse and theoretical feedback were subjected to an AI-assisted hybrid thematic analysis. Primary manual open coding was performed to find subtle theoretical frameworks, namely, isolating themes of the so-called autonomous sonic object and the communicative act, the generational change of digital-native cognition, and manifestations of African musical ontology (e.g., Ibibio functionalism and the vital force of *Ntu*). Subsequently, qualitative data analysis software (ATLAS.ti) integrating Large Language Models (LLMs) was deployed to assist in cross-validating these theoretical nodes against the statistical outcomes of Phase 1.⁴² This synergy guaranteed strong coherence in the explanation of the student data based on the existing expert lenses.

Ethical Considerations

Given the experimental reliance on expectancy violations, stringent ethical safeguards were paramount. The 2×2 factorial design required temporary misleading about the source of the musical excerpts; thus, a detailed debriefing procedure was implemented immediately after data collection.⁴³ This debriefing clarified the methodological imperative of the deception and exposed the actual source of all the stimuli considered. Prior to participation, explicit written informed consent was obtained, clearly delineating the voluntary nature of involvement, the right to withdraw without penalty, and the strict anonymisation of all identifiable data. Furthermore, regarding the qualitative strand (Phase 2), ethical guidelines for internet-based research were strictly adhered to. The qualitative analysis relied on expert discussion obtained via a free, open-access academic database (ResearchGate). Since these professionals shared their knowledge publicly in an open academic discussion in their professional personas, their words are referenced with their real names in line with normal academic attribution conventions of published scholarly discourse, where the pseudonymisation typical of traditional field research is not required. Ethical clearance and research permits were obtained from the University Ethics and Research Committee of the participating universities in accordance with the provisions of the ethical standards governing human-subject research in Kenya.

⁴¹ Marcel Zentner, Didier Grandjean, and Klaus R. Scherer, “Emotions Evoked by the Sound of Music: Characterization, Classification, and Measurement,” *Emotion* 8, no. 4 (2008): 494–521, <https://doi.org/10.1037/1528-3542.8.4.494>.

⁴² J. Z. Bullindah and A. Kula, “Revolutionizing Qualitative Research: The Impact of 'on ATLAS.Ti for Enhanced Data Analysis,” *15th International Music and Performing Arts Conference 2025 Book of Abstracts* (Kabarak University, 2025).

⁴³ Stammer, Strauss, and Knees, “Perception of AI-Generated Music--The Role of Composer Identity, Personality Traits, Music Preferences, and Perceived Humanness.”

PRESENTATION OF FINDINGS AND DISCUSSION

This section presents the empirical findings and theoretical interpretations derived from the mixed-methods explanatory sequential design, investigating the impact of perceived AI authorship on listener emotional resonance. The analysis is based on the *Ngoma* paradigm, which positions African musical arts as a socially embedded institution that must generate vital force (*Roho*), yet goes beyond traditional Western acoustic analyses to question the ontological worth of music as a form of communication. This section adopts a combined thematic approach to enable it to present a coherent and comprehensive narrative. Instead of separating the statistical products from the theoretical framework, the quantitative data produced by the student cohort are synthesised with the qualitative information obtained by the international expert panel (Phase 2). This integrated approach explains both what the listeners experienced and theoretically why they reacted as they did. The main quantitative part of this study adopted a 2×2 factorial deceptive listening experiment to isolate the cognitive bias against algorithmic music versus real acoustic preference. The experiment quantified expectancy violation and the resulting authenticity deficit by manipulating the labelled origins of four matched musical excerpts (Human vs. AI). The section is organised systematically: it starts with the creation of the demographic profile of the unified student body, moves to the unpacking of the descriptive statistics that measure the aesthetic and socio-spiritual penalties associated with the AI label, and concludes with the inferential hypothesis testing (Two-Way ANOVA), including effect sizes and confidence intervals, that clarifies where the algorithmic-music penalty is strongest.

Demographic Profile and Baseline Metrics

The quantitative stage produced a useful and sound sample of 76 undergraduate students ($N = 76$). The study pooled the participants of Kabarak University, Kenyatta University, and the Technical University of Kenya to construct a homogeneous group of young adult listeners. This methodology provided a wide representation of the modern Kenyan worldview of aesthetic values, balancing baseline disparities in music and technical literacy across different fields of study. Treating the respondents as a single demographic pool maximises the statistical power of the experimental design, establishing a reliable baseline to test the overarching cultural assumptions of the *Ngoma* paradigm against modern technological disruptions.

Assumption Checks

Prior to inferential testing, assumption checks were performed on the aggregate emotional-resonance scores across the four track conditions. Shapiro–Wilk tests on the pooled residuals indicated modest departures from normality for several sub-scales, which is common with 7-point Likert data (aggregate $W = 0.977, p = .001$). Levene’s test (median-centred) indicated homogeneity of variance across the four track conditions on the aggregate score ($W = 0.319, p = .812$), with similar homogeneity across the individual GEMS-9 sub-scales (all $ps > .40$). Given the robustness of ANOVA to modest normality violations with balanced cell sizes, parametric analyses were retained; where interpretations depended on borderline results, they are hedged accordingly below.

The Total Emotional Resonance Score

To evaluate the impact of perceived authorship on listener reception, descriptive statistics were calculated for the four experimental tracks. The Total Emotional Resonance Score was computed as the average of each respondent’s 7-point Likert ratings across the seven measurements (Aesthetic Wonder, Nostalgia, Power, Intent, *Roho*/Connection, Utility, and Willingness to Pay). The statistical results were triangulated with the qualitative data obtained through an international panel of musicologists, AI researchers, and cultural theorists to give a comprehensive interpretation of these quantitative outputs.⁴⁴

⁴⁴ D Sergeev, “Can Generative AI Ever Replicate the Socio-Spiritual Dimensions of African Musical Arts?” (ResearchGate, 2026), https://www.researchgate.net/post/Do_audiences_value_music_as_an_autonomous_sonic_object_or_as_a_communicative_act_of_human_intent; M. G Mapaya, “Re: Can Generative AI Ever Replicate the Socio-Spiritual Dimensions of African Musical Arts?,” *ResearchGate*, 2026; E. Akpan, “Re: Can Generative AI Ever Replicate the Socio-Spiritual Dimensions of African Musical Arts?,” 2026.

Table 2: Mean Aggregate Emotional Resonance Scores with 95% Confidence Intervals

Track	Actual Origin	Labelled Origin	Mean (M)	95% CI
Track 1	Human-composed	AI-generated	3.94	[3.57, 4.31]
Track 2	AI-generated	Human-composed	4.12	[3.71, 4.52]
Track 3	Human-composed	Human-composed	4.53	[4.12, 4.94]
Track 4	AI-generated	AI-generated	4.13	[3.74, 4.52]

Note. $N = 76$. Aggregate scores on a 7-point Likert scale.

The descriptive data reveal a preference for the fully authentic human baseline, which evoked the strongest overall emotional response among participants (Track 3, $M = 4.53$, 95% CI [4.12, 4.94]). Notably, and contrary to the results typical of Western research, the explicit labelling of a track as AI did not instigate a catastrophic loss of emotional resonance in the other tracks. Track 4 (Actual AI, Labelled AI) and Track 2 (Actual AI, Labelled Human) achieved nearly identical mean scores ($M = 4.13$ and $M = 4.12$, respectively). Track 1 (Actual Human, Labelled AI) received the lowest aggregate score ($M = 3.94$), consistent with the interpretation that the AI *label*, rather than the actual origin, carries most of the perceptual weight. A Two-Way ANOVA on the aggregate score indicated that neither main effect nor the interaction reached conventional significance (F values ranging from 0.34 to 2.33; all $ps > .12$; partial $\eta^2 \leq .008$), which places the aggregate effect in the small-effect range. This quantitative reality is synthesised below, step-by-step, with expert discourse and African musicological theory.

The DJ phenomenon and the rejection of the ‘Effort Heuristic’

The stability of the scores for the AI-generated tracks—regardless of how they were labelled—challenges established Western literature, such as the “Effort Heuristic” (Kruger et al., 2004), which posits that audiences inherently devalue music lacking human struggle. This statistical pragmatism is anticipated by contemporary African musicologists. According to Mapaya, in the Southern African context, the contemporary phenomenon of DJs has fundamentally changed the expectations of the audience. Mapaya argues that modern audiences “*do not care how authentic the music is,*” prioritising instead whether it provides “*the appropriate soundtrack to their social status.*”⁴⁵ The quantitative data are broadly consistent with Mapaya’s assertion among Kenyan youth: the utilitarian role of the music appears to matter more than the authenticity of its origin, which is one plausible reading of why listeners rated Track 4 comparably to the labelled-human tracks ($M = 4.13$). This is further corroborated by AI researcher Dmitriy Sergeev, who notes a profound generational shift among younger digital-native audiences. Sergeev emphasises that in the case of such a demographic, the communicative component of music is no longer about what the human composer intended to convey but about how the sound makes the listener feel at that moment.⁴⁶ The fact that AI tracks scored comparably to the labelled-human tracks in aggregate resonance suggests that the Kenyan student group is broadly at ease engaging with algorithmic music as an independent sonic experience.

Bridging Formalism and the Communicative Act

This practical assessment invites a philosophical settlement between two contrasting views of music. As Ndonga emphasises, the formalist perspective, associated with Eduard Hanslick, holds that the value of music lies in its internal components (melody, rhythm) as an independent sonic object.⁴⁷ Conversely, Ian Cross defines music as a ‘communicative act’ conveying human intent. The data suggest that Kenyan youth are bridging these concepts. Once Tracks 2 and 4 successfully imitated the internal form of African polyrhythms, they attained comparable aesthetic acceptance. As Gambirasio notes, in a commodified, neoliberal digital landscape, music behaves like an object on a shelf, but it is only streamed “*if it makes*

⁴⁵ Mapaya, “Re: Can Generative AI Ever Replicate the Socio-Spiritual Dimensions of African Musical Arts?”

⁴⁶ Sergeev, “Can Generative AI Ever Replicate the Socio-Spiritual Dimensions of African Musical Arts?”

⁴⁷ J Ndonga, “Re: Can Generative AI Ever Replicate the Socio-Spiritual Dimensions of African Musical Arts?,” *ResearchGate*, 2026.

sense on a communicative level.”⁴⁸ The algorithmic tracks were effective in making themselves aesthetically intelligible to the listeners, without the conventional need for a human sender to establish the communicative relationship.

Functional pragmatism

While this pragmatism aligns with modern consumption habits, it stands in theoretical tension with the conventional African epistemology. As Akpan strictly defines it, in African societies (such as the Ibibio), music is not a mere sonic object, but a communicative act meant for the transfer of ideologies and values.⁴⁹ This aligns with the *Ngoma* paradigm, which conceptualises music as requiring *Muntu* (human intelligence) and *Roho* (spirit). The comparatively pragmatic pattern in these results, then, indicates that modern Kenyan university students interpret the *Ngoma* mandate through a strongly functionalist lens. According to Nzewi, African musical arts operate as the science of sound, a tool designed to generate affective-effective energy for the community.⁵⁰ On this interpretation, if the sound waves themselves are perfect enough to generate that energy and facilitate social utility, the youth demographic accepts the output as valid *Ngoma*. The algorithm, in this modern perspective, acts as a kind of drum: it is a *Kintu* (a non-living object), yet when it emits the right acoustic tones, it can support the social and aesthetic interests of the community, and the biological authenticity of the source becomes secondary to its functionality.

Disaggregating the authenticity deficit

While the aggregate scores suggest a pragmatic acceptance of AI music’s acoustic surface, a granular analysis of the specific GEMS-9 and *Ngoma* metrics reveals a more focused authenticity deficit when the algorithmic origin is known. To assess this psychological penalty, the total emotional-resonance score was disaggregated. The 76 participants’ ratings were examined across three metric groups: Aesthetic Emotions (GEMS-9 sub-scales), *Ngoma* Metrics (Intent and *Roho*), and Functional/Valuation Metrics. Responses were recorded on a 7-point Likert scale (1 = Strongly Disagree, 7 = Strongly Agree).

Table 3: Itemised mean scores for experimental tracks by metric category

Metric Category & Specific Item	Track 1 (H, lab. AI)	Track 2 (AI, lab. H)	Track 3 (H, lab. H)	Track 4 (AI, lab. AI)
Aesthetic emotions				
Wonder	3.57	3.77	4.31	4.09
Nostalgia	3.64	3.68	4.32	4.13
Power (uplifting energy)	4.14	4.31	4.83	4.22
Ngoma metrics				
Intent (storytelling/purpose)	4.15	3.90	4.28	3.96
Roho (human connection/spirit)	3.93	4.23	4.54	4.22
Functional & valuation metrics				
Utility (social effectiveness)	3.90	4.27	4.55	4.06
WTP (willingness to pay)	3.56	4.03	4.34	4.10

Note. *N* = 76. Scores are means on a 7-point Likert scale.

The disaggregated data show a consistent directional penalty on tracks identified as AI-generated (Tracks 1 and 4), and a clear peak on Track 3 (actual human, labelled human) across most sub-scales. Two-Way ANOVAs by item indicated that the interaction of Actual Origin × Labelled Origin reached significance for Wonder ($F(1, 279) = 5.73, p = .017$, partial $\eta^2 = .020$) and Nostalgia ($F(1, 279) = 7.21$,

⁴⁸ A. Gambirasio, “Re: Can Generative AI Ever Replicate the Socio-Spiritual Dimensions of African Musical Arts?” (ResearchGate, 2026).

⁴⁹ Akpan, “Re: Can Generative AI Ever Replicate the Socio-Spiritual Dimensions of African Musical Arts? .”

⁵⁰ Nzewi, “African Music Creativity and Performance: The Science of the Sound.”

$p = .008$, partial $\eta^2 = .025$), which are small effects by conventional benchmarks. For the *Ngoma* metrics and the functional/valuation metrics, the main effects and interaction did not reach conventional significance on this sample (all $ps > .08$). Post-hoc Tukey HSD comparisons among the four tracks per metric did not identify pairwise-significant differences at the FWER-corrected $\alpha = .05$ threshold; Cohen's d values for T1 versus T3 (the sharpest theoretical contrast) ranged from $|d| = 0.30$ (Roho) to $|d| = 0.41$ (Nostalgia), indicating small-to-moderate effects. Taken together, the disaggregated pattern validates the psychological and theoretical tensions surrounding algorithmic music without overstating the sharpness of the statistical result.

The illusion of perfection and the dampening of aesthetic emotion

The Aesthetic Emotion category showed that the listener's subjective perception of beauty and emotional depth is influenced by authorship labels. Track 1, despite being an authentic human field recording, received the lowest scores in Nostalgia ($M = 3.64$) and Wonder ($M = 3.57$) when audiences were told it was generated by a machine. On the other hand, Track 3 (Actual Human, Labelled Human) attained the highest scores across the same items (Wonder $M = 4.31$; Nostalgia $M = 4.32$; Power $M = 4.83$), and the Actual Origin $\times$ Labelled Origin interaction reached significance for Wonder ($F(1, 279) = 5.73$, $p = .017$) and Nostalgia ($F(1, 279) = 7.21$, $p = .008$). This indicates that participants generally gave higher aesthetic ratings to tracks whose labelled and actual origin aligned as "human." Although the main effect of the label alone was not strictly significant, the descriptive similarity between the deceptive AI track (Track 2) and the true human baseline (Track 3) is consistent with the concept of the Musical Turing Test within an African auditory system. The findings corroborate recent empirical research by Figueiredo et al. and industry data from Deezer and Ipsos, confirming that deep-learning models have successfully closed the acoustic gap.⁵¹ The AI successfully replicated the phenomenology of human music, and the significant interaction on the two aesthetic sub-scales suggests that this acoustic perfection is filtered through psychological perception; the cognitive concept of "Human" functions as a booster of aesthetic enjoyment.

The collapse of the Ngoma metrics and the parasocial void

Perceived intentionality and spiritual connection (Intent and *Roho*) exhibited a directional pattern that is consistent with the paper's theoretical claim, although the effects on this sample did not reach conventional significance. The lowest *Roho* score was for Track 1 ($M = 3.93$), while Track 3 (all-human, aligned label) received the highest ($M = 4.54$). The Actual Origin main effect on *Roho* was essentially zero ($F(1, 279) < 0.01$, $p = .963$), and the label effect and interaction did not reach significance ($ps > .17$). This lack of a strong actual-origin effect suggests that the psychological penalty associated with the "AI-generated" label was applied consistently, regardless of whether the source was a human field recording or a digital simulation. The pattern is interpretable through the 'Effort Heuristic'⁵² and the 'parasocial void'.⁵³ Kenyan audiences appear to undervalue creative work when they believe no human struggle or lived experience lies behind it. Read through the *Ngoma* paradigm, this is consistent with an interpretive claim rather than a demonstrated causal effect: because participants believed Track 1 was algorithmic, they reported feeling less spirit in the music, which resembles the classification of a *Kintu* (a lifeless, inanimate object). The pattern of means, rather than the strength of the inferential test, is what supports the theoretical reading here.

Economic and Functional Rejection

The final category assessed the practical utility of the music and the listener's Willingness to Pay (WTP), transitioning the focus from emotional resonance to socio-economic valuation. Descriptively, tracks labelled AI received a directional commercial penalty. Listeners reported lower Willingness to Pay (WTP) for Tracks 1 and 4 ($M = 3.56$ and $M = 4.10$, respectively) than for the human-labelled tracks

⁵¹ Figueiredo et al., "Echoes of Humanity: Exploring the Perceived Humanness of AI Music"; Deezer and Ipsos, *Industry Survey Finds Most Listeners Cannot Tell AI Music from Human Work*.

⁵² Kruger et al., "The Effort Heuristic."

⁵³ Aruwajoye, "Floating Signifiers: AI, Semiotics, and the Crisis of Meaning in Music."

(Track 2 $M = 4.03$; Track 3 $M = 4.34$). The ANOVA indicated that this was a directional tendency rather than a strictly significant primary effect ($F(1, 277) = 3.04, p = .082$, partial $\eta^2 = .011$ for the interaction). For Utility (perceived social effectiveness), the pattern was similar: Track 3 was rated highest ($M = 4.55$) and Track 1 lowest ($M = 3.90$), with the label effect approaching but not reaching conventional significance ($F(1, 279) = 3.69, p = .056$, partial $\eta^2 = .013$). Even without reaching $p < .05$, the consistent directional penalty is culturally interpretable. As articulated by Nzewi (2006), music in this context operates as the “science of sound,” requiring human intent to generate the affective-effective energy necessary for communal cohesion. On this reading, algorithmic music underperforms the functional requirement of *Ngoma*: the loss of authenticity registers not only in personal emotional response but also in the social role and commercial acceptability of algorithmic output. If audiences do not believe a human consciousness is communicating with them, the music tends toward the status of an object rather than a communal tool, softening its perceived market value in the attention economy.

RECOMMENDATIONS

Based on the empirical findings and theoretical synthesis of this study, the following recommendations are proposed for the music industry, cultural policymakers, and academic researchers:

- The directional decline in WTP and *Roho* when music was labelled as AI indicates an underlying psychological preference for authenticity. Streaming platforms such as Spotify and Apple Music, together with generative-AI developers, should implement clear, standardised labelling for fully algorithmic tracks. Deceiving listeners to manufacture parasocial connections is unethical and, once the origin is revealed, economically fragile.
- Given the parasocial void created by fully automated music, developers should shift their design philosophies from creating autonomous artist replacements to designing intuitive co-creation tools. If digital-native listeners can use AI to articulate their own human intent, the technology transitions from a soulless generator into a modern instrument of *Ngoma*.
- The ability of deep-learning models to replicate cultural acoustic patterns without understanding their spiritual context presents a significant threat of ‘digital colonialism.’ Policymakers should establish intellectual-property and data-sovereignty frameworks to prevent the uncompensated scraping of traditional African music (such as Mijikenda or Ibibio heritage) by Western technology conglomerates.
- Because algorithmic music appears to underperform as a ‘communicative act,’ institutions of cultural preservation should actively fund and support live, human-centric musical arts to ensure the continuity of living traditions that AI could otherwise displace.
- This study captured the aesthetic worldview of Kenyan digital natives at a specific inflexion point in technological history. Future research should employ longitudinal designs to observe whether the authenticity deficit narrows over time as algorithmic music becomes increasingly normalised in everyday consumption.
- While this study controlled for educational stratification by focusing on university students, future studies should investigate how older generations or rural populations deeply entrenched in traditional *Ngoma* practices perceive and interact with high-fidelity algorithmic music.

CONCLUSION

This study set out to answer a critical ontological question triggered by the rapid proliferation of generative AI: does the listener care about the human spirit behind the sound? Employing a mixed-methods explanatory sequential design grounded in the African epistemological framework of *Ngoma*, this research investigated whether acoustic indistinguishability equates to artistic value among Kenyan university students. The findings present a layered reality. Descriptively, the fully authentic human baseline evoked the strongest emotional response, and tracks labelled as AI attracted a consistent directional penalty across every metric category. Inferentially, this penalty reached conventional significance in the aesthetic sub-scales of Wonder and Nostalgia, while other sub-scales showed small directional effects that did not clear the standard threshold in this sample.

Read together, the pattern indicates that AI models such as Suno and Udio have effectively closed the acoustic gap at a phenomenological level, but the label of “AI” still carries a perceptual cost, most visible in the aesthetic dimensions and in the *Ngoma* metrics of intent and connection. Through the lens of the *Ngoma* paradigm, algorithmic music is best understood as a *Kintu*: it may perfectly replicate the internal structures of African polyrhythms, but it lacks the *Muntu* (human intelligence and spirit) and deliberate intent required to initiate a genuine communicative act. AI can democratise music production and generate highly functional sonic commodities, but on the evidence assembled here, it remains fundamentally limited in replicating the socio-spiritual dimensions of African musical arts. Audiences still rely on human agency to authenticate their emotional experiences, and the future of music cannot be reduced to purely algorithmic output without weakening the communal bonds that define it.

Limitations

A few limitations should be acknowledged when interpreting the findings. First, the sample was drawn from undergraduate students at three Kenyan universities and cannot be assumed to represent older listeners, non-student populations, or rural communities whose engagement with *Ngoma* traditions may be more embedded in daily life; future research should replicate the design across generational and geographic strata. Second, the 2×2 factorial deception design, while methodologically productive, introduces the possibility of demand characteristics once participants become sensitised to the study’s framing; a between-participants replication would strengthen causal inference. Third, the aggregate emotional-resonance measure is a mean of the GEMS-9 sub-scales, and the short-form GEMS-9 has bounded resolution; future work using expanded item pools or physiological indices of engagement would triangulate the self-report signal. Fourth, the AI stimuli were generated using contemporary tools of the Suno/Udio class; results may not generalise to future generative models whose acoustic and stylistic capabilities exceed those tested here.

BIBLIOGRAPHY

- Akhtar, Mohd Junaid, and Sarita Nagvanshi. “Parasocial Interaction and Virtual Influencers.” In *Redefining the Future of Digital Marketing With Virtual Influencers*, 151–80. IGI Global, 2025. <https://doi.org/10.4018/979-8-3373-0255-3.ch006>.
- Akpan, E. “Re: Can Generative AI Ever Replicate the Socio-Spiritual Dimensions of African Musical Arts? ,” 2026.
- Aruwajoye, K. “Floating Signifiers: AI, Semiotics, and the Crisis of Meaning in Music .” Dartmouth College, 2025.
- Bakenne, Nureni Aremu, and Israel A. Fadipe. “Extra-Mundane Communication in Ayinla Omowura’s Music: Exploring Connections Between a Tool and an Agent.” In *Indigenous African Popular Music, Volume 2: Social Crusades and the Future*, 3–29. Springer, 2022.
- Braun, Virginia, and Victoria Clarke. “Using Thematic Analysis in Psychology.” *Qualitative Research in Psychology* 3, no. 2 (2006): 77–101.
- Bullindah, J. Z., and A. Kula. “Revolutionizing Qualitative Research: The Impact of ATLAS. ti for Enhanced Data Analysis. ” *Ti for Enhanced Data Analysis.*” *15th International Music and Performing Arts Conference 2025 Book of Abstracts*. Kabarak University, 2025.
- Chia, Suqi, Andree Hartanto, and Eddie M.W. Tong. “Do Listeners Devalue AI-Generated Pop Music? Exploring Negative Biases in Listeners’ Responses to AI-Labelled vs Human-Labelled Pop Music.” *Computers in Human Behavior: Artificial Humans* 6 (December 2025): 100217. <https://doi.org/10.1016/j.chbah.2025.100217>.
- Creswell, John W., and Vicki L. Plano Clark. *Designing and Conducting Mixed Methods Research*. Sage Publications, 2017.
- Das, Sanjukta, and Rituparna Kundu. “The Ethics of Artificial Intelligence in Creative Arts: A Comprehensive Review.” *Interdisciplinary International Journal of Advances in Social Sciences, Arts and Humanities* 01, no. 01 (2024): 27–34. <https://doi.org/10.62674/ijjassah.2024.v1i1.003>.
- Deezer and Ipsos. *Industry Survey Finds Most Listeners Cannot Tell AI Music from Human Work*.

Darwin Beats, 2025.

- Eraslan, Ismail. "Artificial Intelligence and the Rewriting of Musical Memory: A Cognitive Perspective." *Science Development* 6, no. 3 (July 28, 2025): 114–20.
<https://doi.org/10.11648/j.scidev.20250603.18>.
- Fetters, Michael D., Leslie A. Curry, and John W. Creswell. "Achieving Integration in Mixed Methods Designs—Principles and Practices." *Health Services Research* 48, no. 6pt2 (December 23, 2013): 2134–56. <https://doi.org/10.1111/1475-6773.12117>.
- Figueiredo, Flavio, Giovanni Martinelli, Henrique Sousa, Pedro Rodrigues, Frederico Pedrosa, and Lucas N Ferreira. "Echoes of Humanity: Exploring the Perceived Humanness of AI Music." *ArXiv Preprint ArXiv:2509.25601*, 2025.
- Gambirasio, A. "Re: Can Generative AI Ever Replicate the Socio-Spiritual Dimensions of African Musical Arts?" *ResearchGate*, 2026.
- Haskins, Casey. "Is AI a Threat to Human Music? (A Neo-Deweyan Perspective)." *The Journal of Aesthetics and Art Criticism* 83, no. 3 (September 23, 2025): 238–53.
<https://doi.org/10.1093/jaac/kpaf024>.
- Kagame, Alexis. *Sprache Und Sein: Die Ontologie Der Bantu Zentralafrikas*. Kivouvou, Ed. Bantoues, 1985.
- Kavusa, J. "Humans and Non-Humans as אדם and Ntu-Beings: Ecological Appraisal of Gen 2:7 and 19 in Dialogue with African-Bantu Indigenous Cosmology." *Old Testament Essays* 35, no. 2 (January 1, 2022): 149. <https://doi.org/10.17159/2312-3621/2022/v35n2a3>.
- Khalfallah, Donia, and Veronika Keller. "Authenticity, Ethics, and Transparency in Virtual Influencer Marketing: A Cross-Cultural Analysis of Consumer Trust and Engagement: A Systematic Literature Review." *Acta Psychologica* 260 (October 2025): 105573.
<https://doi.org/10.1016/j.actpsy.2025.105573>.
- Kirui, Amon Kipyegon, Mellitus N. Wanyama, and Madimabe Geoff Mapaya. "Epistemics of African Music Performance: Navigating Knowledge, Tradition, and the Digital Frontier." *African Musicology Online* 14, no. 2 (June 24, 2025): 14–24. <https://doi.org/10.58721/amo.v14i2.1107>.
- Kruger, Justin, Derrick Wirtz, Leaf Van Boven, and T. William Altermatt. "The Effort Heuristic." *Journal of Experimental Social Psychology* 40, no. 1 (January 2004): 91–98.
[https://doi.org/10.1016/S0022-1031\(03\)00065-9](https://doi.org/10.1016/S0022-1031(03)00065-9).
- Lecamwasam, Kimaya, and Tishya Ray Chaudhuri. "Exploring Listeners' Perceptions of AI-Generated and Human-Composed Music for Functional Emotional Applications." *ArXiv Preprint ArXiv:2506.02856*, 2025.
- Mapaya, M. G. "Re: Can Generative AI Ever Replicate the Socio-Spiritual Dimensions of African Musical Arts?" *ResearchGate*, 2026.
- Ndonga, J. "Re: Can Generative AI Ever Replicate the Socio-Spiritual Dimensions of African Musical Arts?" *ResearchGate*, 2026.
- Nketia, J. H. K. *The Music of Africa*. W. W. Norton & Company, 1974.
- Nzewi, Meki. "African Music Creativity and Performance: The Science of the Sound." *Voices: A World Forum for Music Therapy* 6, no. 1 (March 1, 2006).
<https://doi.org/10.15845/voices.v6i1.242>.
- Rix, Jennifer, Benedikt Berger, Thomas Hess, and Christine Rzepka. "The Algorithm Discount: Explaining Consumers' Valuation of Human- versus Algorithm-Created Digital Products." *Journal of Management Information Systems* 42, no. 2 (April 3, 2025): 633–68.
<https://doi.org/10.1080/07421222.2025.2487308>.
- Rutsate, Jerry. "Ngoma Materiality and Instrumentality: Reconfiguring Malawian Indigenous Music Digitization for Global Music Appreciation." In *De-Neocolonizing Africa*, 449–61. Cham: Springer Nature Switzerland, 2024. https://doi.org/10.1007/978-3-031-66304-8_25.
- Sergeev, D. "Can Generative AI Ever Replicate the Socio-Spiritual Dimensions of African Musical Arts?" *ResearchGate*, 2026.
https://www.researchgate.net/post/Do_audiences_value_music_as_an_autonomous_sonic_object_or_as_a_communicative_act_of_human_intent.

- Soundverse. "The Authenticity Gap: Human Perception and the Aesthetic Valuation of AI-Generated Music," 2025.
- Stammer, David, Hannah Strauss, and Peter Knees. "Perception of AI-Generated Music--The Role of Composer Identity, Personality Traits, Music Preferences, and Perceived Humanness." *ArXiv Preprint ArXiv:2512.02785*, 2025.
- Turing, A. M. "I.—Computing Machinery And Intelligence." *Mind* LIX, no. 236 (October 1, 1950): 433–60. <https://doi.org/10.1093/mind/LIX.236.433>.
- Yende, Sakhiseni Joseph. "Towards a Theory of Indigenosociomusicology: African Perspectives on Indigenous Knowledge, Social Meaning, and Decolonial Music Studies." *Eastern African Journal of Humanities and Social Sciences* 5, no. 1 (2026): 61–71.
- Zentner, Marcel, Didier Grandjean, and Klaus R. Scherer. "Emotions Evoked by the Sound of Music: Characterization, Classification, and Measurement." *Emotion* 8, no. 4 (2008): 494–521. <https://doi.org/10.1037/1528-3542.8.4.494>.
- Zhou, Yongxin, Yuhui Wang, and Jiayu Su. "A Study on Factors Influencing Music Enthusiasts' Behavioural Intention to Use Generative AI for Music Composition Based on an Expanded Technology Acceptance Model." *Scientific Reports* 15, no. 1 (December 29, 2025): 44802. <https://doi.org/10.1038/s41598-025-28532-2>.
- Zlatkov, Dimiter, Jeff Ens, and Philippe Pasquier. "Searching for Human Bias Against AI-Composed Music," 308–23, 2023. https://doi.org/10.1007/978-3-031-29956-8_20.

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