Co-Creating with the Neural Net

Artistic Practice, Pedagogy, and the Ethics of AI in Music and Sound

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Abstract—**This paper argues that Artificial Intelligence (AI) in music is best understood not as the substitution of one author by another but as a redistribution of creative agency across humans, datasets, algorithms, and institutions. This sociocultural claim requires a perceptual counterpart, for which we draw on the construct of situational context (the perceptual mechanism through which listeners attribute agency in mediated sonic events) and its measurable property, expressive fidelity. The novel contribution of the present work is threefold: It links the cultural critique of AI in music to a cognitive-perceptual mechanism that can be assessed in recordings; proposes authorship literacy as a four-component teachable construct; and formulates a research agenda that converts the sociocultural critique into testable claims. We apply the combined framework to three sites of transformation (artistic practice across genres, pedagogy and authorship literacy, and ethics and cultural politics) and formalize a research agenda comprising three empirical questions (preservation, attribution, design) and one reflective question on long-term cultural shifts in how listeners interpret recorded sound. The paper is addressed to two communities. For music researchers, educators, and artists, it supplies a perceptually grounded extension of existing critiques of AI in music. For AI researchers and system designers, it offers a vocabulary in which the perceptual stakes of generative music systems can be made explicit and built into evaluation and design criteria.**

Keywords—co-creation; AI; music technology; authorship; expressive fidelity.

I. INTRODUCTION

Artificial Intelligence (AI) has rapidly become one of the defining technological and cultural developments of the twenty-first century. Within music, AI has expanded from a computational tool into an active participant in artistic creation, education, and cultural production. Machine Learning (ML) systems generate melodies, harmonies, orchestrations, sound synthesis processes, and complete compositions in stylistically recognizable forms, and they increasingly do so in commercial, pedagogical, and live-performance contexts.

The integration of AI into music reflects a broader historical pattern of technological transformation in the arts, in which mechanization, recording technologies, electronic instruments, and digital production tools have each reshaped artistic practice [1]. Contemporary AI extends this trajectory but also intensifies it, because generative systems imitate forms of creative agency previously considered uniquely human, and because their integration is accompanied by unprecedented economic concerns. The 2025 Teosto survey of the Finnish music industry, conducted by Vastakaiku as a follow-up to a 2023 baseline, found that 72% of music professionals hold negative attitudes toward AI in music and that 93% want policymakers to address AI's challenges; only 28% expressed positive views [2]. Comparable concerns have been registered by performing-rights organizations elsewhere, including the joint position of ASCAP, BMI, and SOCAN that training models on copyrighted works without permission, compensation, or credit constitutes theft rather than fair use [26]. The discussion surrounding AI in music is therefore not purely technical but deeply cultural, pedagogical, political, and now regulatory.

This paper argues that AI in music is best understood not as the substitution of one author by another but as a redistribution of creative agency across humans, datasets, algorithms, and institutions. The title, *Co-Creating with the Neural Net*, is intended to capture this position at both ends. Whereas *co-creating* indexes the redistribution-of-agency claim, in which the human author is no longer single-handed, *Neural Net* indexes the specific technical class of generative AI systems, namely deep neural networks trained on large corpora of recorded music, whose appearance in the creative pipeline produces the redistribution under analysis. In view of the foregoing, the novelty of the present contribution may be summarized in three points. First, it links the sociocultural critique of AI in music to a cognitive-perceptual mechanism, *situational context*, that is operationalizable through a measurable property of recordings, *expressive fidelity*. Second, it proposes *authorship literacy* as a four-component teachable construct that endows the pedagogical discussion with a usable curricular target. Third, it formulates a research

agenda that converts the cultural critique into testable empirical claims and design criteria addressed to both music researchers and AI system designers.

The remainder of the paper is structured as follows. Section II develops the redistribution-of-agency framework. Section III introduces situational context and expressive fidelity as the perceptual mechanism and measurable property through which the framework can be grounded and assessed. Section IV applies the combined lens to three sites of transformation, namely co-creation in artistic practice across genres (IV.A), pedagogy and authorship literacy (IV.B), and ethics, copyright, and cultural politics (IV.C). Section V formalizes the research agenda. Section VI closes with conclusions, limitations, and future work.

Methodologically, the present argument proceeds as a theoretical synthesis. No single empirical procedure could meaningfully exhaust the multifaceted character of AI as a creative, pedagogical, and ethical phenomenon. We therefore opt for a mixed conceptual approach in which (a) the relevant research literature in AI music systems, music technology, and music pedagogy is critically reviewed; (b) the construct of situational context, drawn from prior work on recorded sound and ludoacoustic immersion, is integrated as a perceptual lens; (c) preliminary observations from public practitioner discourse are noted as orientation toward hypotheses; and (d) an empirical research agenda is formulated from which the framework's claims may subsequently be tested. No new experimental data are reported here. The contribution of this paper is the framework and the agenda.

II. AI AND THE REDISTRIBUTION OF CREATIVE AGENCY

Historically, computational approaches to music emerged through algorithmic composition practices developed during the twentieth century: Pioneers, such as Iannis Xenakis and John Cage, explored stochastic procedures and indeterminacy long before contemporary machine learning became possible [3]. Early interactive music systems already explored machine listening and responsive compositional interaction decades before contemporary generative AI became mainstream [4]. Current AI systems differ substantially from these earlier rule-based methods because they rely on large-scale datasets and probabilistic modelling. Herremans, Chuan, and Chew propose that music generation systems can be categorized according to their functional roles, ranging from stylistic imitation to fully autonomous generative processes [5]. Across this spectrum, generative systems increasingly participate in musical decisions traditionally associated with human composers: Harmonic progressions, melodic material, orchestration strategies, and real-time performative interactions. The conventional relationship between composer and instrument becomes destabilized, and AI systems function not as passive tools but as agents that actively shape aesthetic outcomes [6].

Authorship, in AI-mediated music, is no longer locatable in a single human originator. It is distributed across the human composer or prompter, the dataset on which a model has been trained, the algorithmic architecture that shapes generative behavior, and the institutions that curate corpora and deploy systems. AI-mediated composition resembles collaborative artistic practice more than conventional instrumental usage [6], yet the collaborators in question include datasets and architectures whose contribution is harder to circumscribe. Miranda emphasizes that computer-assisted composition should not necessarily replace human creativity but instead expand possibilities for musical experimentation and structural design [7]. Reframed through redistribution, this expansion shifts the role of the artist toward curation, conceptual framing, critical intervention, and system design.

This kind of redistribution is neither unprecedented nor terminal: Earlier disruptions, such as synthesizers and digital production tools, ultimately expanded musical practice while opening new ones [8]. AI differs, however, in one respect that matters: Algorithmic creativity remains deeply dependent on pre-existing cultural material, since AI systems are trained on datasets that reflect human musical histories and institutional biases, and AI-generated outputs may reproduce dominant aesthetic norms while marginalizing less-represented traditions [9]. The redistribution of agency is, in other words, not symmetrical across the network. Audience experiences are likewise reshaped: AI-assisted performances foreground process, emergence, and instability, so that listeners encounter music as an evolving negotiation between human and machine agency [10]. Among the experiential outcomes implicated by this shift is immersion, the listener's sense of being situated within a sonic world that responds coherently to its own internal logic. If creative agency is distributed across a longer chain of mediating systems, the question of how listeners attribute that agency, and how immersion holds or fails, becomes an empirical one rather than a metaphor.

This is where existing accounts run short. The redistribution of creative agency is a claim about how authorship is structured. It does not yet say how that structural change is perceived in the act of listening. To bridge that gap, the next section turns to a construct from research on recorded sound that supplies a perceptual mechanism for agency detection, together with the measurable property by which that mechanism can be assessed, and we propose that both can be productively transposed to the AI context.

III. SITUATIONAL CONTEXT AND EXPRESSIVE FIDELITY: A BRIDGING CONSTRUCT

To address the gap identified at the close of Section II, we draw on a theoretical construct from research on recorded sound: *situational context*, the perceptual mechanism through which listeners infer agency in mediated sonic events, and *expressive fidelity*, the measurable property of recordings by which situational context is supported or undermined [21]. The two terms operate at different levels. Situational context is the cognitive-perceptual process through which agency attribution occurs in the act of listening. Expressive fidelity is the property of the recording that affords or interrupts that process. Holding the distinction allows the present argument to advance both a theoretical claim about how listeners perceive AI-mediated sound and

an empirical claim about what can be measured in the recordings themselves.

In any sonic event, three agents are implicated: An actor whose state of mind is the source of expressive intention, the object through which that intention gets materialized as physical action, and the environment that responds to and shapes that action through its acoustic properties. During listening, only the object-environment exchange is directly audible. The actor's state of mind is inferred from the way that exchange unfolds. Situational context, in this view, is the listener's running construction of who is acting on what within what space, generated through continuous comparison between expectations about object-environment interaction and the incoming acoustic stimulus [22][23]. Expressive fidelity is the recording-side property that determines whether the cues required for that construction are present at sufficient resolution.

Where expressive fidelity is preserved, listeners attribute coherent agency: A performer's intention becomes legible through the resonances of the space in which the performance is captured. Where it is degraded or simulated unconvincingly, situational context fails to consolidate, and listeners default to alternative attributions, often perceiving the sound as artificial or as belonging to an indeterminate source. These responses are not arbitrary. They depend on acquired *artifact literacy*: The learned conventions by which listeners interpret the trace of object-environment interaction in recorded media [24].

Situational context is also one of the perceptual mechanisms by which recorded sound affords immersion. The listener's sense of being situated within a sonic environment depends not only on the surface features of sound (timbre, dynamics, spatial cues) but on the coherence of the interaction syntax those features carry. A recording with high expressive fidelity invites the listener's embodied perceptual schemata to project the virtual situational context of the recording onto the real situational context of the listener's own surroundings, producing the sense of inhabitation variously described as presence, immersion, or non-mediation [25]. This projection is what allows recorded sound to function as more than a technical artifact of capture: It is the basis on which a recording becomes a situational world the listener can inhabit.

The relevance of this two-level construct to AI-generated music follows from a structural transposition. In its original formulation, the chain runs from actor to object to environment, with the listener inferring intention from the object-environment exchange. In AI-mediated music, the chain extends and complicates. A generative model has been trained on a dataset of recordings, each of which carries or fails to carry expressive fidelity to varying degrees. The model produces outputs that may preserve, transform, or collapse the interaction syntax carried by its training data. A human prompter or curator shapes the conditions of generation. The listener encounters the final output without direct access to most of these intermediate stages. The same agency-detection machinery is operating, but on a profoundly altered signal chain. What gets attributed to whom, and because of what acoustic evidence, becomes an open question. Figure 1 illustrates both chains side by side.

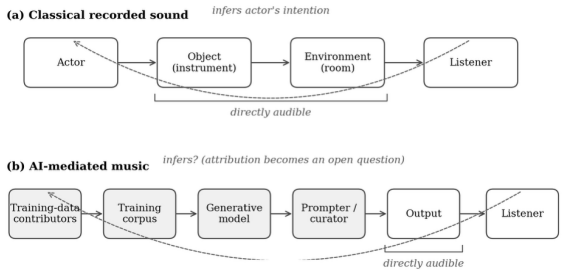

Figure 1. **Figure 1.** The actor-object-environment chain in (a) classical recorded sound and (b) AI-mediated music. The AI-mediated chain extends through training-data contributors, corpus, generative model, and prompter; only the final output remains directly audible.

This conceptual bridge connects the sociocultural redistribution of creative agency with the perceptual processes through which listeners attribute agency in AI-mediated music. Situational context provides the perceptual mechanism, while expressive fidelity provides a measurable property through which that mechanism can be assessed. Together, they establish a framework that links cultural theory, perceptual analysis, and AI system design, providing the foundation for the applications and research agenda that follow.

IV. THREE SITES OF TRANSFORMATION

The combined framework of redistributed creative agency and situational context is now applied to three interconnected domains in which AI is actively reshaping musical culture.

A. Co-creation in Artistic Practice

In contemporary classical practice, David Cope's Experiments in Musical Intelligence (EMI) [11] and George Lewis's Voyager [12] illustrate contrasting modes of dispersed authorship: EMI generated stylistically recognizable works raising questions about originality and emulation, while Voyager demonstrates AI as an improvisational partner. The two projects place different demands on situational context, since batch-generated scores and real-time interactive systems require distinct kinds of expressive fidelity to sustain listener agency attribution. Film music, where AI increasingly supports rapid prototyping and orchestration under tight production schedules, presents the sharpest situational-context implications, since film scoring depends acutely on the listener's projection of virtual situational context onto a diegetic world.

In video game music, adaptive and procedural audio systems have long distributed sonic agency across designer rules, runtime logic, and player input, well before contemporary generative AI entered the field. Researchers, including Karen Collins [13] and Gasselseder [14], have examined how these algorithmic systems contribute to immersive gameplay by allowing soundtracks to evolve with

player behavior, narrative progression, and environmental variables. The dominant middleware (FMOD, Wwise) remains rule-based; procedural audio in the synthesis tradition is algorithmic, not learned. Generative AI is a more recent layer that extends rather than originates this redistribution, entering game audio at specific points, such as generative music within adaptive systems, ML-driven voice synthesis, and ML-assisted mixing. Game audio thus has decades of experience with the redistribution of audio agency across non-human systems, a continuity that itself argues against treating AI as historically unprecedented. Situational context and expressive fidelity were originally operationalized in this adaptive-audio setting, which makes the integration of generative models into adaptive pipelines precisely the case the present paper formalizes.

Popular music production has similarly absorbed AI-assisted technologies for beat generation, vocal synthesis, mastering, and songwriting support, with AI-generated tracks imitating recognizable artists generating controversy regarding copyright and artistic identity. Holly Herndon's Spawn [15] approached AI as a collaborative process foregrounding embodiment and collective authorship, while systems including OpenAI's Jukebox, Google's Magenta, and Sony CSL's Flow Machines [16] illustrate the variety of generative approaches. Flow Machines' contribution to "Daddy's Car" demonstrates how generative systems can emulate popular aesthetics while raising authorship questions that the situational-context lens makes empirically tractable.

B. Pedagogy and Authorship Literacy

The incorporation of AI into music education has introduced new pedagogical possibilities while challenging established educational paradigms. AI-assisted learning systems can provide immediate feedback on rhythm, pitch, harmony, and performance accuracy, enabling individualized experiences that adapt to learner needs [17]. Adaptive platforms may also democratize access to compositional and analytical tools that previously required extensive institutional resources, allowing learners to experiment with orchestration, harmonic analysis, sound design, and generative composition through accessible interfaces.

The pedagogical challenge, however, extends beyond efficiency and accessibility. Music education has historically emphasized embodied knowledge, instrumental practice, and long-term skill development, and AI-generated content risks encouraging passive consumption rather than active creative engagement if used uncritically. In response, educators face the task of developing what we term *authorship literacy*: The capacity to understand and critically engage with how AI systems function as agents in the production of music. Authorship literacy extends the longer tradition of computational and media literacy in education [18] into a setting where the chain of mediation has lengthened beyond the conventions audiences and creators have absorbed informally.

Authorship literacy is the pedagogical sibling of *artifact literacy*, the construct introduced in earlier work on recorded sound to name the learned conventions by which listeners interpret the trace of object-environment interaction in recordings [24]. Where artifact literacy describes what audiences acquire through exposure, authorship literacy describes what learners must be taught explicitly. We propose four interlocking components.

Analytical literacy concerns understanding how generative systems operate: What training data conditions a model, how stylistic features are statistically derived, where the limits of generation lie, and what biases and absences shape outputs. *Perceptual literacy* concerns the trained capacity to attend to interaction syntax in mediated sound, to recognize where situational context consolidates or breaks down, and to interpret the perceptual artifacts that signal algorithmic mediation. *Ethical literacy* concerns the origins of training corpora, the labor and consent conditions of dataset construction, and the practices of attribution, transparency, and credit that follow. *Critical literacy* concerns the capacity to evaluate AI outputs against artistic, cultural, and ethical criteria rather than treating algorithmic plausibility as a self-justifying standard.

These components imply curricular shifts. Technical proficiency in AI tools is necessary but not sufficient; learners also require analytical access to how the tools work, perceptual training in how AI mediation registers in the audible material, ethical framing, and critical vocabularies for evaluating outputs. Educators thus mediate not only between students and instruments but between students and the algorithmic systems that increasingly shape musical practice. AI also reshapes accessibility, since individuals without formal conservatory training can now engage with compositional processes through intuitive interfaces, an expansion that authorship literacy is the construct to make deliberate rather than incidental.

C. Ethics, Copyright, and Cultural Politics

The most debated issues regarding AI-mediated music involve copyright and authorship along with concerns about sustainability and economic viability. Current laws and regulations were formulated based on the notion of human authorship. Since the outputs of a generative system are produced on a probabilistic basis from training datasets composed of copyrighted musical works [19], it can be argued that generative systems do not comply with these laws and regulations. Copyright holders assert that training data must not be built on copyrighted works without authorization. In addition, even when a generative system's output does not reproduce existing works in the data, there are risks that the stylistic nuances associated with individual composers are reproduced through the statistical extraction of expressive content in the data [22].

Within the framework and situational context, there is an additional dimension to copyright: The question becomes not only what kinds of material generative systems might produce or reproduce on a surface level but also what they might capture or extract from the interaction syntax of human-made recordings. Training data preserves expressive fidelity of sound. The question of whether or not generative systems preserve that same fidelity, or whether they strip down such material to its statistical surface, determines

whether what is reproduced is musical agency or its de-facto shadowing of the real.

Such a framing has implications for licensing, attribution, and the distribution of remuneration, since these may not be attuned to what is actually captured or extracted from human-made recordings and transferred to listeners. Bias enters for related reasons. Training datasets tend to reflect social inequalities, and generative systems may reproduce or even exacerbate them, for instance through overrepresentation of Western tonal traditions. Beyond representation, bias shapes which forms of expressive fidelity are preserved and which are omitted, so that the agency of some musical traditions becomes legible through AI mediation while that of others is flattened.

Regulatory frameworks have begun to address these concerns. The European Union's AI Act (Regulation (EU) 2024/1689), fully applicable from August 2026, places transparency and copyright-related obligations on providers of general-purpose AI models under Article 113 [27], including a public summary of training content and disclosure requirements for AI-generated audio; an associated Code of Practice was published by the European Commission in June 2026 [28]. Read through the framework, these provisions begin to render the actor-object-environment chain auditable: The training-data summary makes visible what corpora a model has ingested, while the labelling obligations disclose to the listener that AI is in the signal path.

The framework suggests three directions for intervention beyond disclosure. First, opt-out and opt-in registries allowing rightsholders to determine whether their recordings enter training corpora, with audit mechanisms tied to the AI Act's training-data summary requirement. Second, expressive-fidelity preservation as a design criterion for model evaluation, motivating training-data curation that retains object-environment interaction syntax rather than merely acoustic surfaces. Third, listener-facing disclosure mandates that close the asymmetry between what the system knows about its pipeline and what the listener can attribute. Taken together, these sketch what a perceptually grounded ethics for AI in music could look like in practice.

Generative systems also offer assistance and support, for instance through adaptive interfaces for disabled musicians or by lowering the threshold for experimental practice. Ethics here demands nuance rather than technological determinism. At the same time, unequal access to AI infrastructure risks reinforcing global asymmetries, since wealthier institutions can develop proprietary systems with proprietary training data and capture more value. Generative systems thus challenge the romantic notion of artistic genius rooted in individual originality: Creativity appears more accurately as a distributed network of human, technological, datasetal, and institutional contributors [20]. Such a reframing situates human agency more honestly within the mediating structures through which humans have always participated in music-making.

V. A Research Agenda: From Framework to Empirical Questions

The framework of Section II and the situational-context construct of Section III together open a set of empirical questions that neither account would generate alone. Preliminary observations from practitioner communities suggest these questions address real perceptual experiences: In forums such as r/audioengineering, vi-control.net, and Gearspace, commentary on generative AI music converges on descriptors - "soulless," "hollow," "fabrication" - consistent with degraded expressive fidelity and failed situational-context consolidation, while a vocal minority reports the inverse, attributing greater coherence to AI outputs. Whether the perceived deficit disappears without knowledge of AI involvement directly motivates the attribution question below. We propose three empirical questions and one reflective question, each formulated so that hypotheses about expressive fidelity function as concrete handles on what AI mediation does to situational context.

The preservation question. Do generative music models preserve the expressive fidelity of their training data, or do they collapse object-environment interaction syntax into surface features? Architectures optimized against surface-level losses may produce outputs that pass evaluation while losing the cues through which situational context consolidates. Comparative acoustic analyses of matched human and AI outputs - room-response coherence, reverberation-tail behaviour, spatial-cue stability - provide tractable handles. The question determines whether what is transferred from human creators through training pipelines to listeners is the substance of musical agency or its degraded shadow.

The attribution question. How does the actor-object-environment chain restructure when listeners know or suspect AI involvement? Between-subjects designs with matched stimuli and disclosure manipulation test whether agency attribution and immersion ratings shift even when the audible material is held constant. The question matters because it tests whether the perceptual machinery operates independently of cultural framing, or whether knowledge of AI mediation actively reshapes how the chain is constructed in listening.

The design question. Can generative systems be designed to preserve or simulate expressive fidelity, and does this improve perceived agency or immersion? Candidate interventions include multi-perspective training corpora retaining object-environment interaction syntax, interaction-aware architectural constraints, and curation criteria beyond surface acoustic quality. Comparative evaluations against unmodified baselines yield design guidance that converts the framework from critique into an actionable design heuristic.

A fourth question exceeds the time horizon of any single study. As listeners accumulate exposure to AI-generated music, the priors on which expressive fidelity rests - the learned conventions of artifact literacy - may themselves shift. AI does not only produce outputs; over time it rewrites the perceptual conventions through which all recorded music is heard. We raise this as a reflective question rather than an

empirical proposal, since the relevant comparisons unfold over years. Its implications are ethical as much as perceptual, and connect to the cultural-politics concerns of Section IV.C.

The agenda addresses two audiences. For music researchers, it offers empirical handles, perceptual measures, and listening-study designs that bring the cultural critique into the regime of testable claims. For AI system designers, it offers evaluation criteria beyond surface-level loss metrics, training-data curation grounded in what is perceptually load-bearing, and a design vocabulary in which expressive fidelity is treated as a property to be preserved rather than an accident of training data.

VI. Conclusion and Future Work

This paper has argued that AI in music is best understood as a redistribution of creative agency across humans, datasets, algorithms, and institutions, and that this sociocultural claim requires a perceptual counterpart. We have proposed situational context as the perceptual mechanism and expressive fidelity as its measurable property, applied the combined framework to artistic practice, pedagogy, and ethics, and formalized a research agenda. The novel contribution is a vocabulary that music researchers and AI system designers can both adopt. Limitations remain: Expressive-fidelity preservation has not been empirically measured here; the situational-context construct has been operationalized only in adaptive-audio contexts [21]; authorship literacy has not been tested in classroom settings; and the preliminary practitioner observations of Section V are drawn from technically literate online communities.

Future work proceeds along ranked priorities. The preservation question constitutes the empirical bottleneck, since both the design and attribution questions presuppose it. Preservation studies should be conducted on matched human and AI outputs across the genre cases of Section IV.A, drawing on measures such as room-response coherence, reverberation-tail behaviour, and spatial-cue stability. Second-priority work addresses attribution through between-subjects listening studies with disclosure manipulation; third, design-question work proceeds in collaboration with AI system designers. Three challenges deserve acknowledgment: Bridging humanities-style critique to engineering-style empiricism requires sustained interdisciplinary collaboration; the EU AI Act and analogous frameworks remain in early implementation; and empirical work on AI in music is increasingly concentrated in well-resourced institutions. The cultural critique of AI in music is most useful when paired with a perceptual mechanism and a measurable property that the relevant communities can act upon.

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