The Role of Artificial Intelligence in Electroacoustic Score Generation: A Review

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ABSTRACT

Electroacoustic music—marked by nonlinear temporal structures, complex timbral materials, and non-standard notational practices—poses persistent challenges for representation, performance, and dissemination. This article offers a critical thematic review of how artificial intelligence (AI) shapes electroacoustic score generation across three primary domains: symbolic, spatial, and gestural. We survey contemporary approaches—symbolic modeling, deep generative methods, gesture mapping, and spatial trajectory prediction—and clarify their musical affordances and limits. We introduce a purpose-first taxonomy and three focused case discussions to deepen analysis without expanding scope. Alongside technical considerations, we foreground authorship, performer agency, interpretability, and aesthetic control, and examine ethical concerns around data bias, cultural specificity, and creative homogenization. We argue that AI's potential is strongest when systems are designed transparently and inclusively and when practices are collaborative, interdisciplinary, and reflexive. By synthesizing developments with philosophical inquiry, we outline pathways for responsible, imaginative integrations of AI in electroacoustic music.

1. INTRODUCTION

1.1. Topic Overview

Electroacoustic music, emerging from mid-twentieth-century experimental practices, diverges from traditional acoustic paradigms in both material and method. Defined by its reliance on recorded, synthesized, or transformed sound—often dislocated from physical instruments—this genre often emphasizes timbral, spatial, and gestural dimensions over pitch and meter. Composers in this domain, such as Edgard Varèse and Pierre Schaeffer, reimagined the score not as a static representation of notes, but as a dynamic system responsive to sonic transformation and performer interaction [1, 2].

However, despite its innovative sonic vocabulary, electroacoustic music remains constrained by a persistent and unresolved issue: the lack of widely standardized, legible, and expressive score systems. Unlike traditional staff notation, which is codified and widely understood, electroacoustic works often employ a pluralism of representations—graphic scores, animated systems, gestural maps, or software interfaces—that are often bespoke, ambiguous, and performatively opaque [3, 4]. These systems can struggle to convey critical parameters such as spectral morphologies, spatial trajectories, or nonlinear form [5], which can place interpretive burdens on performers and complicating reproducibility, pedagogy, and archiving [6].

In this landscape of notational fragmentation, artificial intelligence (AI) emerges as a promising but under-examined approach. AI techniques, particularly those rooted in machine learning, generative modeling, and gesture analysis, can facilitate the translation of complex sonic or spatial data into interpretable forms. They can support tools not only for symbolic rendering but also for dynamic, multimodal, and co-creative score systems that reflect the real-time, embodied, and spatial dimensions of electroacoustic practice [7, 8].

1.2. Purpose and Scope of the Review

This article presents a critical thematic review of AI's role in electroacoustic score generation, with a focus on how intelligent systems may address the core problem of notational insufficiency. The review is structured around the following three research questions:

- *How can AI facilitate the generation of symbolic, spatial, and gestural scores that are interpretable by performers and composers?*
- *What are the current limitations and potentials of AI systems in transcribing, modeling, or generating scores for non-pitched and electroacoustic sound materials?*
- *How does the integration of AI reshape traditional assumptions about authorship, creativity, and performance in electroacoustic music?*

To anchor these questions, Table 1 below offers a taxonomy of electroacoustic score types and the corresponding roles AI may play in their generation, adaptation, or interpretation. We classify by primary function—visual/temporal guidance, body/physical interaction, and spatial localization—with other aspects treated as secondary dimensions. This typological overview frames the subsequent sections and identifies key intersections between score formats and AI technologies

Primary function	Score Type	Key Features	Challenges	AI Role	References
Visual/Temporal Guidance	Graphic Scores	Visual symbols, lines, shapes, textures	Ambiguity, lack of visual vocabulary	Image-to-audio translation, visual-sound mapping	[1, 9, 10]
Visual/Temporal Guidance	Symbolic Scores (MIDI/Staff)	Discrete pitch/rhythm representations	Inadequacy for noise-based or spatial material	Fuzzy logic, symbolic abstraction from spectral data	[11, 12]
Visual/Temporal Guidance	Animated / Real-Time Scores	Time-evolving visualizations	Performance alignment, computational complexity	Generative score engines, real-time gesture and audio tracking	[5, 9, 13]
Body/Physical Interaction	Gestural Maps	Motion-capture, haptic or physical cues	Interpretive burden, sensor calibration	Gesture recognition, AI-based motion-to-sound mapping	[14-16]
Spatial Localization	Spatial Scores	Diffusion cues, trajectory maps, multi-speaker configurations	Representation of space and movement	Trajectory prediction, spatial interpolation, multimodal data alignment	[17-19]

Table 1. Taxonomy of Score Types in Electroacoustic Music and Related AI Roles

This taxonomy illustrates the diversity and complexity of electroacoustic score formats while highlighting how AI can mediate the translation between sonic data, visual representation, and human interpretation. The remainder of this review explores these intersections in depth, organized around symbolic generation, audio transcription, deep generative models, spatial/gestural integration, and critical reflection on authorship, legibility, and ethics.

This review contributes to both scholarly and compositional discourses by mapping out the current state of AI-assisted score generation and identifying paths toward more inclusive, legible, and expressive electroacoustic music practices.

2. FOUNDATIONS: ELECTROACOUSTIC MUSIC AND SCORE REPRESENTATION

This section establishes the representational frame for the taxonomy that follows. Electroacoustic practice often privileges timbre, spatialization, and gesture, which can strain conventional staff notation. In response, composers use a range of alternative formats—graphic, animated/real-time, gestural, and spatial—each with distinct affordances and limitations for composition and performance. To clarify where AI may assist, we map these formats and the challenges they pose for automation and interpretation.

2.1. Characteristics of Electroacoustic Composition

Electroacoustic practice motivates score formats that convey not only sonic structure but also embodied, spatial, and performative parameters [19]. The diversity of sound materials—granular synthesis, spectral morphing, noise, diffusion—can resist symbolic transcription, placing additional demands on representation and rehearsal. These considerations motivate alternative score systems beyond staff notation, each with distinct affordances and limitations that will be situated by the taxonomy in Table 1 and developed in the sections that follow.

2.2. Evolution of Notation in Electroacoustic Practice

The earliest electroacoustic works were often realized in studios and lacked formal scores altogether, being presented as fixed media recordings [20]. When scores were used, they consisted of verbal instructions, timing charts, or circuit schematics, intended more for technical execution than artistic interpretation [1], reflecting a composer-as-technician model, where the score served engineering more than performance.

By the late twentieth century, composers adopted *graphic scores* to convey more subjective or spatially emergent phenomena. These scores relied on lines, shapes, and colors to suggest dynamics, movement, and texture rather than precise pitches [9]. Yet their *semantic openness* often led to widely divergent performances, depending heavily on performer interpretation [5]. In response, *animated scores* were developed using software environments that could display evolving instructions in real time. Eigenfeldt's real-time notation engine and systems like GNMISS [9] allowed performers to interact with time-sensitive gestures and environmental cues. These systems expanded the expressive range of scores but introduced new requirements for screen-based interaction and performer adaptability [13].

Recent practice integrates symbolic notation, gestural input, and spatial representation to create multimodal environments in which performers interpret pitch, movement, and space as integrated data streams [14]. However, integrating multiple data types into a coherent interface remains an open design challenge.

2.3. Connecting to AI Integration

Each score type presents *distinct opportunities for AI intervention*. Symbolic scores align with AI's strengths in rule-based generation and symbolic abstraction [11]. Graphic and animated scores open pathways for image-to-audio learning, temporal prediction, and visual feature extraction [10]. Gesture-based and spatial scores present opportunities for *sensor-driven input*, pattern recognition, and spatial behavior modeling [14].

As we move forward, the diversity of score formats require equally diverse AI strategies, with an emphasis on *co-design between composers, systems, and performers*. The next sections explore these intersections in detail—evaluating how AI supports symbolic rendering, real-time performance, generative co-creation, and spatial or gestural intelligence in electroacoustic score systems.

3. OVERVIEW OF ARTIFICIAL INTELLIGENCE IN MUSIC

Artificial Intelligence (AI) has become increasingly central to contemporary music creation, offering new methodologies for composition, performance, analysis, and interaction. Its impact spans both traditional symbolic domains (e.g., MIDI, score notation) and audio-based processes, with applications ranging from harmonic modeling to spatial audio rendering. For electroacoustic music, where sound exists beyond conventional pitch-rhythm syntax, AI offers unique affordances for abstraction, transformation, and multimodal integration.

3.1. Core AI Paradigms and Music Applications

AI in music operates through three dominant paradigms: rule-based systems, machine learning (ML), and deep learning (DL). Early systems relied on rule-based logic—such as heuristic or constraint-based models—to encode compositional procedures [11]. While transparent and controllable, these models lacked flexibility when addressing nonlinear or textural sound structures typical of electroacoustic music.

By contrast, machine learning models learn from examples. Trained on musical corpora, they extract statistical patterns to generate stylistically coherent outputs [21]. Within this paradigm, deep learning, including convolutional and transformer-based neural networks, enables high-dimensional feature learning and abstraction—crucial for capturing gestural, spectral, or affective elements in music [22]. Rule-based systems are transparent yet inflexible for nonlinear or textural materials, while ML/DL approaches depend on training data and can be opaque in attribution.

3.2. Symbolic vs. Audio Approaches

AI systems in music are generally categorized as symbolic or audio-based, but practice often hybridizes both; we use this distinction heuristically. Symbolic approaches—using representations like MIDI or MusicXML—are effective in tonal or rhythmically regular domains. They support melodic generation, chord progressions, and formal structuring [12]. However, symbolic models often falter in electroacoustic contexts, where sonic identity may not conform to pitch or rhythmic quantization [4].

Audio-based systems, which work directly with raw or processed sound, bypass the limitations of notation. These include spectrogram-based models, waveform autoencoders, and audio-domain transformers that generate or transform textures, timbres, and gestures without requiring symbolic intermediaries [21]. This capacity is especially vital for electroacoustic music, where expressive material exists in continuous spectral and temporal dimensions. Symbolic models can falter when sonic identity resists quantization, while audio-domain methods bypass notation yet can raise interpretability and real-time constraints.

3.3. AI in Creative and Compositional Practice

AI has moved from static score generation toward interactive and co-creative systems. Generative models—like those powering Magenta, MusicLDM, and FlowMachines—can produce stylistically nuanced music based on training data [10]. These tools enable composers to explore variant forms, novel combinations, or data-informed aesthetics.

Increasingly, AI models are designed for real-time performance and improvisation. For instance, Donohue+ responds dynamically to live musicians, generating interactive electroacoustic accompaniments based on performative cues [23]. This positions AI not as a static tool, but as an improvisational partner, shifting the composer-performer-AI triad toward shared agency.

AI has also been incorporated into emotionally responsive systems, where affective computing drives the generation of music aligned with user input or mood [22]. These models open new pathways for affective engagement, adaptive environments, and therapeutic applications. Co-creative systems remain shaped by their training data, may shift perceived agency among composer–performer–system, and must meet practical responsiveness for performance.

3.4. Pedagogical and Analytical Functions

In educational contexts, AI enables personalized learning and exploration. Tools such as those developed in the EARS 2 project provide students with interactive environments to experiment with sound transformation, symbolic abstraction, and spatial composition [24]. Similarly, Cooper highlights how AI can assist in curriculum design, compositional scaffolding, and assessment—particularly in complex fields like electroacoustic music [25].

From an analytical perspective, AI aids in pattern recognition, gesture detection, and score–audio alignment, providing insights into structural and perceptual dimensions that are difficult to extract manually [11].

Ethical and cultural considerations—including dataset transparency, bias, and inclusion—are consolidated in section 6.

3.5. Summary: AI Capabilities in Electroacoustic Contexts

To conclude, the main affordances of AI in music—particularly for electroacoustic composition—can be summarized as follows:

Compositional/performative affordances

- Symbolic Generation: Automated score production from style-trained models [12].
- Audio Transformation: Textural/spectral manipulation without symbolic mediation [21].
- Gesture Recognition: Mapping physical motion to control sound or notation [14].
- Real-Time Interaction: Responsive systems for live performance [23].
- Affective Adaptation: Emotion-aware composition tools [22].

Analytical/pedagogical affordances

- Educational Support: Interactive, AI-informed learning platforms [25].
- Score-Audio Mapping: Analytical alignment of non-standard scores to sonic outcomes [13].

The sections that follow examine these affordances in relation to symbolic modeling, spatialization, and gestural performance within electroacoustic score generation.

4. AI FOR ELECTROACOUSTIC SCORE GENERATION

Artificial Intelligence (AI) presents both opportunities and complexities in resolving the longstanding challenges of score generation for electroacoustic music. Given the genre's resistance to standard notation—due to its use of textural, non-pitched, spatial, and gestural elements—AI systems serve not merely as tools for translation, but as collaborators in encoding and interpreting ephemeral sonic content. This section critically evaluates the major AI approaches currently applied to electroacoustic score generation, examining their technical affordances, artistic viability, and interpretive challenges.

4.1. Symbolic Modeling and Score Abstraction

AI-based symbolic modeling typically involves mapping features such as pitch, onset, or dynamics to MIDI or staff notation formats. In electroacoustic contexts, however, the translation of sound into symbolic terms can risk oversimplification (see section 2). Traditional symbolic systems are poorly suited for representing spectral morphologies, spatial behaviors, or gestural nuances inherent to electroacoustic composition [1].

To mitigate this misalignment, researchers have explored fuzzy-logic and probabilistic approaches. For example, a fuzzy-rule-based framework can interpret higher-level abstractions—such as timbral brightness or gestural envelope—yielding a more flexible symbolic representation. [12]. While such models can improve the capture of ambiguous sonic content, their interpretability remains limited. The resultant scores often require significant post-editing by composers to become performable or legible [6].

More broadly, symbolic AI still privileges discrete events over continuous transformations. Electroacoustic works built on glissandi, spectral smearing, or convolution are fundamentally resistant to fixed symbolic codification. This raises the question: should AI strive for symbolic fidelity, or embrace hybrid systems that integrate symbolic, visual, and gestural layers? The latter path appears more promising but remains underexplored [26].

4.2. Audio-to-Score Transcription

AI transcription systems aim to extract notational data from raw audio. While effective in tonal and percussive contexts, such systems can struggle with the ambiguity of electroacoustic textures. Techniques like onset detection, spectral centroid tracking, and gesture inference—often powered by neural networks—have improved in precision [13], but can still fall short when confronted with dense, noisy, or non-repetitive material [6].

Moreover, transcription often produces notations that are technically accurate but aesthetically or semantically irrelevant. A granular synthesis cloud, for example, may be transcribed as a rapid sequence of micro-onsets, misrepresenting its perceptual continuity [1]. Without human-in-the-loop design and co-design (see section 4.4), such systems risk creating scores that are unfaithful to the composer's intent and unperformable in practice [9].

While some systems integrate gesture tracking (e.g., motion capture, sensor input), these mappings often suffer from cultural and contextual ambiguity. A raised arm might signify a crescendo in one context, but trigger spatial diffusion in another. AI can struggles to disambiguate such mappings without contextual learning or supervised training [5, 15]. This reveals a major limitation: gesture fidelity is highly dependent on co-design between AI developers and performers, a relationship still in its infancy.

4.3. Deep Generative Systems (GANs, VAEs, Transformers)

Generative Adversarial Networks (GANs), Variational Autoencoders (VAEs), and transformer-based architectures have recently been employed to generate scores, spectrograms, and gestural abstractions. These models are particularly effective in stylistic emulation and the generation of novel content from latent spaces [21].

For example, MusicLDM—a transformer-based model—has been used to interpret visual graphic scores and generate audio responses[10]. This approach circumvents the need for symbolic notation by producing temporal sonic gestures from abstract visual inputs. The strength of such models lies in their ability to handle nonlinear and ambiguous material—a trait ideal for electroacoustic media.

These systems present interpretability and dataset-dependence constraints: GANs are often opaque [11]; VAEs can reduce output resolution; and Transformers depend heavily on the training corpus, which can replicate dominant stylistic features [21, 27]. Taken together, these issues can yield smeared or overgeneralized gestures and contribute to creative homogenization, complicating validation and control [11, 21, 27]. These concerns echo broader critiques of AI in art: who is really composing—the model, the training data, or the curator?

4.4. Spatial & Gestural Encoding

4.4.1.Spatial encoding

One of the most promising frontiers is the application of AI to spatial dimensions of score generation. Electroacoustic music frequently involves sound movement through multichannel environments—features that can resist conventional notation. AI has been used to track, predict, and generate spatial trajectories using tools such as ambisonics, speaker diffusion algorithms, or spatial interpolation models [17, 19].

4.4.2.Gestural mapping

In gestural contexts, AI can interpret physical movement—via accelerometers, depth cameras, or wearable sensors—and map these to sonic transformations or score events [14, 28]. These systems enable embodied composition, aligning physical gesture with acoustic feedback in real-time.

4.4.3.Limitations and calibration

However, these mappings are not universally intuitive. AI often lacks the semantic context to interpret a gesture's expressive intent. Furthermore, reliance on real-time tracking introduces issues of latency, false positives, or misclassification, particularly in performance settings with high variability [5, 29].

The future lies in co-adaptive systems—where AI not only learns from human gesture but allows for correction, nuance, and iterative refinement by performers and composers alike. Such designs, however, require deeper collaboration between musical and technical domains.

4.5. Comparative Synthesis: Evaluating AI Techniques for Electroacoustic Score Generation

AI-assisted electroacoustic score generation remains an emerging and multifaceted field. While current systems show promise across symbolic, spatial, and gestural domains, each approach comes with distinct limitations in legibility, fidelity, and creative control. The most effective tools tend to be those that *combine AI automation with human feedback*, supporting a hybrid process of co-creation rather than full automation. Future progress will depend not just on technical innovation, but on sustained interdisciplinary collaboration and ethical reflexivity.

AI Technique	Effectiveness	Technical Readiness	Interpretability	Main Limitations
Symbolic Modeling	Moderate (good for stylized input)	High	Moderate to High	Poor handling of gestural/textural elements
Audio Transcription	Low to Moderate (varies by texture)	Moderate	Low	Misrepresents continuous sound; lacks semantic intent
GANs / VAEs	High (for abstract or style-based tasks)	Moderate	Low	Opaque logic; poor generalization across domains
Transformers (e.g. MusicLDM)	High (especially for visual/audio integration)	Moderate to High	Moderate	Bias from training data; creative homogenization
Gesture-Based Systems	High (with human co-design)	Moderate	High (when transparent)	Ambiguity of meaning; high variability in input
Spatial AI Models	High (in controlled environments)	Moderate	Moderate	Latency; performer-dependency; needs calibration

Table 2. Comparative Evaluation of AI Techniques for Electroacoustic Score Generation

5. PLATFORMS, TOOLS, AND EXAMPLES

The development of AI-driven tools for electroacoustic score generation has accelerated in recent years, producing a growing ecosystem of platforms that support compositional, performative, and pedagogical applications. These tools vary significantly in terms of input modalities, output formats, and user engagement, ranging from symbolic modeling environments to real-time gesture-responsive systems. This section offers a structured overview of key platforms and cross-references case studies that demonstrate their real-world application.

5.1. Overview of Platforms

Several prominent platforms have emerged that integrate AI into music creation and score generation.

Google's Magenta uses deep learning models such as recurrent neural networks (RNNs) and transformers to generate symbolic and audio data, often in the form of MIDI sequences. While designed primarily for general musical tasks, its modularity allows adaptation for experimental and electroacoustic uses [11].

Sony's FlowMachines uses constraint-based AI to model stylistic patterns, focusing on automatic composition and accompaniment generation. It excels in generating stylistically coherent symbolic outputs but is less suited for the gestural and spatial demands of electroacoustic music [21].

IRCAM's OpenMusic provides a visual programming interface for algorithmic and symbolic composition. While not AI-native, it can be extended with machine learning modules and supports integration with gesture-tracking or spatial audio tools [11].

Specialized platforms such as GNMISS (Graphical Notation for Mixed-Input Score Systems) are tailored specifically for real-time score rendering in electroacoustic and telematic settings. It supports live input and dynamic visualization, emphasizing performance interaction [9]. Similarly, Eigenfeldt's real-time notation engine adapts score material based on performer behavior, facilitating a dialogic relationship between system and performer [13].

Gesture-sensitive systems like those link physical movement to musical transformations, often using sensors like Wii remotes, depth cameras, or accelerometers [5, 14]. These systems serve not only in live performance but also as potential sources of score generation through motion mapping and AI classification.

In the domain of spatial music, platforms combine spatial audio rendering with AI-driven spatialization control, enabling trajectory planning and diffusion automation across speaker arrays [17, 18].

Platform	Input Type	Output	Application Area
Magenta (Google)	MIDI, symbolic sequences	Symbolic/music/audio (MIDI, Wave)	Style emulation, generative composition
FlowMachines (Sony)	Musical constraints, corpora	Symbolic music	Stylistic modeling, automatic composition
OpenMusic (IRCAM)	Algorithms, data flow, symbolic inputs	Notation, score structures	Algorithmic composition, gesture-spatial links
GNMISS	Audio, performer input	Dynamic graphical score	Live electroacoustic performance
Eigenfeldt's Notation Engine	Performer behavior, real-time input	Animated score	Responsive live notation
Gesture Systems	Motion data	Control signals, score fragments	Gesture-informed generation/performance
Rossetti & Manzolli / Kang	Spatial coordinates, audio features	Diffusion cues, trajectory maps	AI-enhanced spatial scoring

Table 3. Comparison of AI-Based Platforms for Electroacoustic Score Applications

5.2. Case Studies and Applications

A number of case studies illustrate how these platforms are deployed in artistic and research contexts. MusicLDM, a transformer-based model, was used to interpret Cardew's Treatise, a canonical graphic score. [10]. The system mapped visual forms to audio gestures, allowing performers to engage with AI-generated material in real time. This case underscores AI's potential to act as a semantic intermediary between abstract notation and sonic output.

Another example is Donohue+, an improvisational accompaniment system that listens to live input and generates responsive electroacoustic textures [23]. Here, AI functions as a real-time co-performer, making decisions based on gesture, phrasing, and timing. The improvisational model reinforces AI's utility not as a composer per se, but as an adaptive, interactive agent within live settings.

In educational settings, the EARS 2 project [24] integrates AI-based modules to help students engage with sound transformation, symbolic representation, and compositional experimentation. While less generative in scope, EARS 2 demonstrates how AI can scaffold access to the conceptual complexities of electroacoustic music.

5.3. Synthesis: Comparative Insights

These platforms collectively highlight a shift in AI's role from content generator to creative interlocutor. Magenta and FlowMachines are strongest in stylistic modeling but lack adaptability to the real-time, embodied dynamics of electroacoustic performance. OpenMusic and GNMISS, while more flexible in input modalities, rely heavily on user customization and integration with external systems.

The most promising applications, such as Donohue+ and MusicLDM, underscore the importance of real-time responsiveness, multimodal input, and semantic adaptability. These systems suggest that AI's strength lies in its ability to facilitate hybrid workflows—merging symbolic, spatial, and gestural modalities—rather than replacing human creativity.

However, limitations remain. Most platforms require extensive setup, lack standardization in score output, and demand high user expertise. Furthermore, gesture and spatial systems still face interpretive challenges and can misrepresent expressive intent if not carefully co-designed with performers.

While no single platform offers a comprehensive solution, the collective landscape of tools illustrates an emerging framework for AI-assisted electroacoustic composition. Future development must prioritize usability, cross-platform interoperability, and collaborative design to ensure these tools serve diverse artistic and educational communities.

6. AESTHETIC AND PHILOSOPHICAL CONSIDERATIONS

The integration of artificial intelligence into electroacoustic music composition brings not only technical innovation but also profound aesthetic and philosophical challenges. These questions—long embedded in experimental music—are now intensified by machine agency, generative unpredictability, and blurred authorship. This section explores these tensions from both composer and performer perspectives, emphasizing the need for critical engagement with emerging creative paradigms.

6.1. Authorship and Creative Agency

AI complicates traditional notions of authorship by distributing creative agency across human and non-human systems. In electroacoustic music, where composers often design systems rather than discrete musical texts, AI further diffuses the role of the composer into curator, co-editor, or system-tuner [30]. Generative models, particularly those based on deep learning or transformer architectures, can produce stylistically coherent outputs without direct human specification, raising the question: who is the composer?

While some argue for understanding AI as a sophisticated tool [27], others view it as a creative collaborator, particularly when its behavior is context-sensitive, unpredictable, and capable of adaptation [11]. Systems like Donohue+ exemplify this ambiguity, where AI responds to live performers with improvisational agency, challenging hierarchical notions of authorship [23].

At the same time, the aesthetic trajectory of AI-generated outputs is shaped by training data. Models often reflect stylistic biases—echoing dominant forms, harmonic conventions, or culturally normative gestures—raising concerns about homogenization and the loss of artistic specificity [31]. Thus, while AI expands creative possibilities, it also embeds invisible constraints, subtly steering compositional decisions.

6.2. Performer Interpretation and Legibility

Performers face their own set of challenges when engaging with AI-generated or mediated scores. Electroacoustic music already demands alternative literacies—reading graphic scores, interpreting spectrograms, or navigating gestural interfaces. AI adds further complexity: dynamic, evolving scores can resist fixity, while transcription models may oversimplify noise-based or gestural content into misleading symbolic forms [4].

Real-time systems shift the performer's role toward that of a responsive interpreter, requiring improvisatory fluency and system familiarity (see sections 4.2, 5.1). In some contexts, performers must *listen to* or *perform with* the AI itself, co-creating outcomes that vary with each realization. This reconfigures the score not as a fixed directive but as a negotiation space between human and machine intentions.

Such shifts raise questions of rehearsal practice, performative agency, and artistic identity. When scores change during performance or are generated live, criteria for fidelity and interpretation shift toward responsiveness and negotiated control within hybrid human–AI ensembles. Related philosophical considerations about authorship, score status, interpretation, and embedded aesthetics are discussed in sections 6.1 and 6.3.

6.3. Critical Hybrid Aesthetic

We use the phrase critical hybrid aesthetic to denote hybrid human–AI mediation that is legible to performers and audiences and foregrounds ethics and performer/composer agency. The philosophical implications of AI in electroacoustic music are not merely abstract—they shape how works are conceived, rehearsed, and received. Composers are increasingly confronted with questions of transparency, intent, and disclosure. Performers, in turn, navigate shifting forms of agency, often learning new interpretive frameworks without standardized notation.

Rather than resolving these tensions, a more productive path lie in embracing the critical hybrid aesthetic—one that acknowledges AI as part of a distributed creative ecology while foregrounding human intentionality, cultural context, and ethical reflexivity. Berkowitz frames creativity as relational, layered, and co-evolving [30].

In this light, the score becomes a site of dialogue between composer and performer, human and machine. Ambiguity persists but can be productive, enabling collaborative authorship and expanded musical imagination.

7. FUTURE DIRECTIONS AND OPEN QUESTIONS

The integration of artificial intelligence into electroacoustic score generation opens a complex, interdisciplinary research frontier—technologically promising but conceptually unsettled. While tools for symbolic generation, spatialization, and gesture recognition have advanced, many questions remain regarding usability, cross-cultural relevance, and artistic coherence. Future development must extend beyond system design into empirical evaluation, critical theory, and collaborative experimentation.

7.1. Hybrid Notation and System Integration

One of the most compelling directions for future work lies in the development of hybrid notation environments—systems that seamlessly merge symbolic, graphic, spatial, and gestural modalities. These environments will require advanced multimodal machine learning to correlate sonic, visual, and motion data in real time, enabling scores that are both expressive and interpretable [14, 26].

Such systems might integrate AI-assisted symbolic abstraction with spatial trajectory mapping and live gesture recognition, rendered through responsive score interfaces. The potential for adaptive scores—which modify themselves in response to performance context—offers exciting possibilities for real-time co-creation. However, this vision demands robust usability testing, performer feedback loops, and design frameworks that prioritize clarity and creative agency.

Agenda: hybrid-notation and system-integration studies.

7.2. Performer-Centered and Audience Studies

To date, most AI–electroacoustic systems have been evaluated through composer or developer lenses. There is a critical need for performer-centered research that investigates how musicians interpret AI-generated scores, navigate real-time systems, and negotiate creative control [5, 9].

Equally important are studies of audience reception, particularly in works involving generative or non-repeatable elements. How do listeners perceive musical authorship, affective coherence, or spatial immersion in AI-mediated performances? Addressing these questions will enrich our understanding of how AI reshapes not just creation, but also perception and meaning making.

Agenda: performer-centered studies and audience-reception studies.

7.3. Cross-Cultural and Inclusive Frameworks

Most current AI systems are trained on Western musical corpora and built within Eurocentric aesthetic frameworks [31]. This poses a risk of cultural homogenization and the marginalization of alternative sonic practices. Future research should prioritize cross-cultural collaboration, dataset diversification, and the design of tools that reflect varied conceptions of sound, gesture, and structure.

AI-assisted systems must be shaped by inclusive values, offering ways to engage with idiomatic instruments, oral traditions, or nonlinear temporalities. Such approaches not only address ethical concerns but also expand the expressive capacity of AI in music.

Agenda: cross-cultural and inclusive framework studies.

7.4. Evaluation Metrics and System Transparency

Finally, a crucial methodological frontier involves developing new evaluation metrics for AI-assisted composition. Traditional metrics (e.g., tonal accuracy or rhythm matching) are insufficient for electroacoustic works. Instead, we must consider affective coherence, performative fluidity, spatial intelligibility, and artistic novelty. Transparent, explainable AI models—those that reveal how decisions are made—will be essential for composer trust and performer adaptation [30, 32].

Agenda: evaluation-metrics and system-transparency studies.

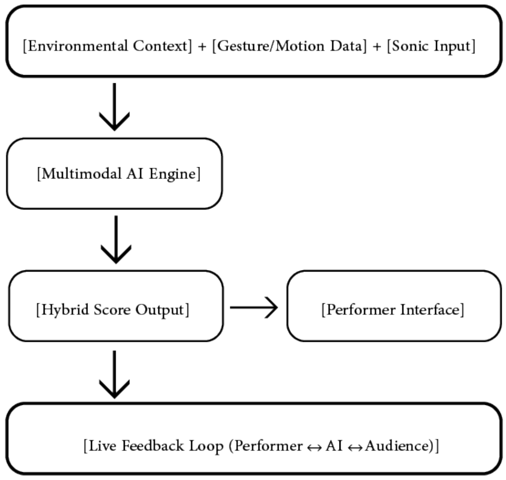

Figure 1. Conceptual Workflow for Future AI-Electroacoustic Systems

- **Sonic Input**: Audio features from live or recorded sources.
- **Gesture/Motion Data**: Captured via sensors or cameras.
- **Environmental Context**: Includes spatial configuration, emotional intent, or audience feedback.
- **Multimodal AI Engine**: Interprets and integrates data into generative decisions.
- **Hybrid Score Output**: Visual or symbolic content rendered for performance.
- **Live Feedback Loop**: Adaptive changes informed by performer and audience behavior.

As AI technologies continue to evolve, the most meaningful progress will come not from algorithmic novelty alone, but from interdisciplinary collaborations that center artistic experience, cultural equity, and critical reflection. The next chapter of AI in electroacoustic music will be written not just by machines, but by communities of makers, listeners, and thinkers committed to expanding what music—and musical authorship—can mean.

8. CONCLUSION

Artificial intelligence has emerged as a powerful force in electroacoustic score generation, capable of transforming the ways composers conceive, notate, and perform sound. Through symbolic modeling, audio-to-score transcription, real-time gesture interpretation, and deep generative systems, AI offers technical support to many of the genre's longstanding challenges, such as the representation of non-pitched material, spatialization, and performer interactivity.

Yet limitations remain. Current systems often struggle with noise-rich, gestural, or culturally specific content that resists abstraction into pitch or rhythm. Hybrid notation environments remain largely experimental, requiring new performer literacies and clearer design frameworks. Deep learning models also risk opacity, reinforcing stylistic biases embedded in training data.

As AI continues to redefine the boundaries of musical authorship, notation, and performance, the guiding imperative is clear: design systems not only to innovate, but to preserve cultural plurality and creative agency.

9. REFERENCES

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