International Journal of Social Science, Arts and Humanities Research

Vol. 1, No.01; Feb 2026

Algorithmic Composition: Artificial Intelligence and Generative Methods in Music

Belikova Viktoriia
Independent Researcher, New Port Richey, USA

Received: Jan 16, 2026 Accepted: Jan 19, 2026 Online Published: Feb 04, 2026

Abstract

This article examines algorithmic composition as a field that employs computational procedures and generative methods to create musical material and complete works. Particular attention is given to artificial intelligence (AI) and its role in contemporary music generation. The paper reviews key paradigms, including rule-based and expert systems, Markov models, evolutionary (genetic) algorithms, and deep learning approaches for symbolic music. Methodologically, the study is based on a structured narrative review of peer-reviewed literature and selected foundational monographs, with emphasis on how models represent musical structure, how outputs are evaluated, and where limitations remain. The analysis highlights trade-offs between controllability, stylistic fidelity, novelty, and structural coherence, and discusses how evaluation practices affect claims of "creativity" and "quality" (Herremans et al., 2017; Yang & Lerch, 2020; Ji et al., 2023). The article also addresses human–machine co-creation workflows and outlines ethical issues related to authorship, labor, dataset provenance, and copyright. Finally, it identifies directions for further research, including improved evaluation protocols, richer forms of musical control, and more transparent documentation of training data and creative intent.

Keywords: Algorithmic composition; artificial intelligence; generative music; machine learning; deep learning; music analysis; composition; neural networks; musical style; creativity.

Introduction

Music has undergone continuous transformation across history, reflecting cultural change, technological development, and evolving artistic practices. In the last decades, a new wave of innovation has emerged at the intersection of music, computing, and artificial intelligence (AI). Algorithmic composition—often referred to as generative music—designates approaches in which computational procedures generate musical material and, in some cases, complete works. These approaches offer composers new opportunities for experimentation, partial automation, and systematic exploration of large design spaces (Herremans et al., 2017).

In contemporary practice, AI can function not only as a tool for automating repetitive tasks but also as a generator of candidate musical ideas, textures, and forms. Rather than manually specifying every event, a composer may define high-level constraints, rules, or objectives and delegate the production of musical material to a system operating within those specifications. This shift has encouraged new workflows in which the composer becomes a curator and editor, evaluating outputs, shaping constraints, and refining structure and expression.

The aim of this article is to investigate algorithmic composition as a technological and aesthetic phenomenon, analyze key AI-based approaches to music generation, discuss evaluation and methodological challenges, and consider ethical questions related to authorship and responsible use.

1. Historical Background and Preconditions of Algorithmic Composition

The idea of generating music according to formal rules predates digital computing. Mechanical instruments and rule-governed procedures demonstrated that musical material could be produced under predefined constraints. The modern era of algorithmic composition began with digital computers and early computational experiments in sound synthesis and pattern generation, followed by specialized software and programming environments that enabled flexible musical modelling.

One historical trajectory emphasized explicit rules and grammars for producing music that conforms to particular theoretical constraints. Another trajectory focused on probabilistic methods, such as Markov models, which generate sequences based on learned transition probabilities and can reproduce stylistic tendencies present in a training corpus (Shapiro & Huber, 2021). These approaches established a foundation for later AI-driven systems by framing composition as the production of structured sequences under constraints.

2. Algorithmic Composition in the Contemporary Context

Contemporary algorithmic composition is shaped by advances in AI and machine learning, especially in symbolic music generation and, increasingly, audio-domain generation. The major families of approaches below differ in representational assumptions, controllability, and the kinds of musical structure they can produce (Herremans et al., 2017; Ji et al., 2023).

2.1 Rule-Based and Expert Systems

Rule-based systems encode stylistic constraints and compositional heuristics as explicit rules derived from music theory or expert knowledge. Their strengths include transparency and controllability; their limitations include difficulty scaling to rich stylistic complexity and the risk of predictable outputs when rules are narrow or insufficiently expressive (Nierhaus, 2009).

2.2 Markov Models

Markov models generate musical sequences by modeling transition probabilities between events (e.g., pitches, intervals, chords, durations). They are relatively easy to train and can produce stylistically plausible local sequences; however, they often struggle with long-range coherence and large-scale form unless supplemented with additional structure or constraints (Shapiro & Huber, 2021).

2.3 Evolutionary and Genetic Algorithms

Evolutionary methods treat composition as a search problem in which candidate musical artefacts are iteratively refined through selection, mutation, and recombination. Fitness functions may be defined by theoretical rules, computational proxies, or human evaluation. These approaches can be effective for exploring large spaces and balancing multiple objectives, but outcomes depend strongly on representation choices and fitness design, and evaluation can be labor-intensive (Gartland-Jones & Copley, 2003; Göksu et al., 2005).

2.4 Deep Learning Approaches

Deep learning has substantially expanded generative capacity in music by modelling complex distributions over musical sequences and capturing higher-order dependencies. Architectures used in symbolic generation include recurrent neural networks and newer sequence modelling approaches discussed in recent surveys (Ji et al., 2023). Deep learning models can yield convincing stylistic outputs, but they raise challenges related to controllability, interpretability, data provenance, and evaluation validity (Herremans et al., 2017; Yang & Lerch, 2020).

2.5 Human–Machine Collaboration

Algorithmic composition is not necessarily oriented toward replacing the composer. In many workflows, AI functions as a generative assistant: it proposes candidate materials, variations, and textures, while the human agent provides artistic intent, selection, contextual framing, and final editing. This division of labor can accelerate ideation and enable exploration of alternatives that would be costly to produce manually (Herremans et al., 2017).

3. Methodology

This article uses a structured narrative review approach. Sources were selected to represent (a) foundational paradigms in algorithmic composition, (b) peer-reviewed surveys of music generation methods, and (c) peer-reviewed research focused on evaluation and human perception of AI-generated music.

3.1 Selection Criteria

Included works met at least one of the following criteria:
1. authoritative surveys or taxonomies of music generation systems;
2. peer-reviewed research on evaluation of generative music;
3. peer-reviewed research on core paradigms (Markov, evolutionary, deep learning) with relevance to algorithmic composition;
4. peer-reviewed research on perception and acceptance of AI-composed music.

3.2 Analytical Procedure

The analysis compared approaches along five dimensions:
1. musical representation (events, structure, hierarchy);

2. degree of controllability and constraint specification;
3. capacity for local and global coherence;
4. evaluation methodology (objective metrics, listening tests, qualitative assessment); ethical implications (authorship, labor, copyright, provenance).

4. Research and Discussion

A central challenge in algorithmic composition research is that improvements in generative capacity do not automatically translate into musically meaningful progress. Claims of "quality," "creativity," or "stylistic success" depend on evaluation design, baseline selection, and transparency of data and constraints (Yang & Lerch, 2020). Recent literature emphasizes that evaluation should combine objective measures with carefully designed human listening studies, and should report limitations and failure modes rather than only successful examples (Yang & Lerch, 2020; Yin et al., 2023).

4.1 Evaluation of Generated Music

Evaluation practices vary widely: some studies rely on informal listening, others on controlled experiments, and others on computational proxies. However, objective metrics alone may fail to capture musical meaning, while subjective evaluation requires resources and can be sensitive to framing effects (Yang & Lerch, 2020). Research on perception shows that contextual information can influence how audiences evaluate AI-composed music and attribute value or agency to the system (Hong et al., 2022).

4.2 Coherence, Form, and Control

Many systems succeed at generating locally plausible sequences (e.g., stylistic melodic fragments) but struggle with long-range form. Surveys of symbolic music generation highlight ongoing efforts to improve structural modelling, enforce constraints, and provide controllable generation that supports compositional intent (Herremans et al., 2017; Ji et al., 2023). These issues are not merely technical: they affect whether a composer can meaningfully shape outcomes and whether results can function as complete works rather than short demonstrations.

4.3 Novelty, Imitation, and Creative Risk

Algorithmic composition often involves a tension between stylistic fidelity and novelty. Systems trained on corpora may reproduce learned regularities; increasing novelty may reduce stylistic coherence. A critical perspective therefore, requires explicit reporting of training data, stylistic objectives, and the intended artistic function of the output, rather than treating "generation" as a single uniform goal (Herremans et al., 2017; Zhao et al., 2025).

5. Ethical and Aesthetic Issues and Future Directions

AI use in music raises ethical questions about authorship, labor, and intellectual property. If a system generates substantial portions of a work, authorship may be distributed across dataset

creators, model designers, and the end user. Ethical practice, therefore, requires transparency about training data provenance, licensing, and the extent of human contribution.

Another major concern involves professional practice: AI-assisted generation may alter demand for certain forms of musical labor and reshape production pipelines. Responsible adoption requires mechanisms that protect creators' rights and avoid misleading audiences about how music was produced.

Future research directions include:

1. more rigorous and comparable evaluation protocols (Yang & Lerch, 2020; Yin et al., 2023);
2. improved controllability and interpretable constraint systems that support compositional intent (Herremans et al., 2017; Ji et al., 2023);
3. clearer documentation standards for datasets, model usage, and authorship roles (Zhao et al., 2025);
4. broader research on listener perception and context effects in evaluating AI music (Hong et al., 2022).

Conclusion

Algorithmic composition is a dynamic field reshaping contemporary conceptions of music creation and creativity. AI-driven generative methods expand the toolkit available to composers and can support new workflows of exploration and co-creation. At the same time, meaningful progress depends on rigorous methodology, transparent reporting, and credible evaluation frameworks that connect technical outputs to musical and cultural value (Herremans et al., 2017; Yang & Lerch, 2020). Ethical issues—especially those related to dataset provenance, authorship, and professional impact—must be addressed alongside technical advances to ensure responsible and sustainable development of AI in music.

List of References

Gartland-Jones, A., & Copley, P. (2003). The suitability of genetic algorithms for musical composition. *Contemporary Music Review, 22*(3), 43–55. https://doi.org/10.1080/0749446032000150870

Göksu, H., Sürer, E., & Yilmaz, C. (2005). Music composition using genetic algorithms (GA) and artificial neural networks (ANN). In *Artificial Intelligence and Applications* (pp. 1–8). Springer. https://doi.org/10.1007/11539902_158

Herremans, D., Chuan, C.-H., & Chew, E. (2017). A functional taxonomy of music generation systems. *ACM Computing Surveys, 50*(5), Article 69. https://doi.org/10.1145/3108242

Hong, J.-W., Fischer, K., Ha, Y., & Zeng, Y. (2022). Human, I wrote a song for you: An experiment testing the influence of machines' attributes on the AI-composed music evaluation. *Computers in Human Behavior, 131*, 107239. https://doi.org/10.1016/j.chb.2022.107239

Ji, S., Luo, J., & Yang, X. (2023). A survey on deep learning for symbolic music generation. *ACM Computing Surveys*. https://doi.org/10.1145/3597493

Nierhaus, G. (2009). *Algorithmic composition: Paradigms of automated music generation*. Springer. https://doi.org/10.1007/978-3-211-75540-2

Shapiro, I., & Huber, M. (2021). Markov chains for computer music generation. *Journal of Humanistic Mathematics, 11*(2), 167–195. https://doi.org/10.5642/jhummath.202102.08

Wang, X. (2024). A comprehensive study on algorithm-based music generation. In *Proceedings of ICMLCA 2023*. ACM. https://doi.org/10.1145/3650215.3650365

Yang, L.-C., & Lerch, A. (2020). On the evaluation of generative models in music. *Neural Computing and Applications*. https://doi.org/10.1007/s00521-018-3849-7

Yin, Z., et al. (2023). A comparative evaluation of algorithms for automatic music generation. *Machine Learning*. https://doi.org/10.1007/s10994-023-06309-w

Zhao, Y., Yang, M., Lin, Y., Zhang, X., Shi, F., Wang, Z., Ding, J., & Ning, H. (2025). AI-enabled text-to-music generation: A comprehensive review of methods, frameworks, and future directions. *Electronics, 14*(6), 1197. https://doi.org/10.3390/electronics14061197