**Machines Making Music: Innovations and Ethical Considerations in AI-Assisted Music Production**

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1. **Abstract**

This article explores the role of artificial intelligence (AI) in contemporary music production and delivery systems. For this literature review, the author collected 80 sources from Google Scholar and the Association for Computing Machinery database and was guided by a research question that asks if music must be a human art form, or if it can be meaningfully created in collaboration with machines. It uses qualitative coding methods to group and analyze the literature, and then organize sources according to the following three themes: (1) generative AI tools for music composition, (2) algorithmic recommendation systems, and (3) ethical considerations around access and bias. These themes make up the discussion portion of this article. The first theme investigates how platforms like digital audio workstations (DAWs) and coding tools such as Sonic Pi and TidalCycles allow users to exert control over the musical output they produce, and how these applications perform the function of multiple instruments. The second theme addresses how AI recommends music to users while at the same time responding to criticisms about originality and creativity in AI-generated musical compositions. The third theme considers digital tools as a double-edged sword in musical production, one which can increase access in some instances, but also exclude users due to cost, disability, or cultural biases. These themes then lead the author to conclude that AI for music production is neither all-good or all-bad, and that combining human creativity with the power of machines can lead to further inclusive innovation within the world of music.

Keywords*:* Artificial Intelligence, Music, Coding, Algorithms, Computer Science

1. **Introduction**

Whether it is the crescendo-building tune in the opening of the *Star Wars* saga, or the airy, delicate quality of “Hedwig’s Theme” from the *Harry Potter* films, there are some songs that are instantly recognizable. What is it about these songs that allows them to resonate with the human experience in such a way that they make an enduring mark in our collective cultural history and public memory? Some would argue that it is the humanistic fingerprint left on these works of art that makes them not only irreplicable and one-of-a-kind, but as exerting an immeasurable societal impact. This article sets out to explore this assumption by researching literature addressing both the merits of and pitfalls of merging advances in computer science with musical production and delivery. The research question guiding these examinations asks, “Is music as an art form a fundamentally human endeavor, or should it be?”

By introducing this question and seeking to respond to it through empirical studies, this article aims to contribute to ongoing conversations regarding the role of artificial intelligence (AI) in society. Through a methodical and comprehensive examination of the academic literature on this topic, this article will argue against an either-or view of AI that presents it as wholly good or definitely bad and instead aims to offer a more balanced understanding of both the possibilities and limitations of digital technologies (AI included) in the production of artistic content. To begin, this article describes the methodology behind this literature review, which involved using qualitative coding to generate three overarching themes from a dataset of 80 articles. The discussion section included after introduces each of these three themes: (1) digital audio workstations (DAWs), (2) coding platforms, and (3) ethical debates surrounding the use of digital technologies for music creation and delivery. It concludes by proposing the next steps forward as the fields of computer sciences and music become more integrated, suggesting a hybridized, collaborative model for computer-human music creation.

All of this is done to offer a more holistic view of AI in musical production and curation, one that neither attempts to perpetuate an already prevalent narrative that portrays AI as loathsome, ominous, or an outright threat. Acknowledging the possibilities that lay within AI’s applications in music, as well as its limitations, in this way is what ultimately will lead to more ethical, inclusive, and accessible innovation.

1. **Methods**

To add to the scholarly conversation on the integration of AI and music production, the author used Google Scholar and the Association for Computing Machinery (ACM) databases to conduct a comprehensive literature review of this topic. The author selected Google Scholar due to the breadth of its coverage, and the fact that it includes many interdisciplinary articles not strictly related to computer science. The ACM Digital Library, on the other hand, was selected as a complementary database because of the sheer number of peer-reviewed publications specifically related to computer science publications it hosts. This approach encompassing both more general studies of computer science and digital music as well as more specific ones helped to ensure that the scope of this review was both broad and sufficiently focused.

To create the dataset for this review, the author used the following search terms to browse these databases: *AI and music, music production and artificial intelligence, computer-generated music, digital audio workstation, live coding, algorithmic composition,* and *machine learning in music*. The results were not filtered by year to combine current perspectives with a historical overview of the development and innovations in this field. Additionally, because computer science is considered a very applied field, no filters were imposed on publication type; this way, trade publications and non-academic sources could be included as well. To lean into the applied focus of the field, the author also excluded all discussions that were solely theoretical in nature. Articles written in a language other than English were also not included in the dataset. Since the data for this review came from existing publications, there were no concerns for ethical research conduct.

1. **Results**

This search resulted in a total of 80 eligible sources, consisting of peer-reviewed journal articles, books, conference proceedings, and technical or industry reports. To ensure that the sample was not skewed towards one field of study or another, it was evenly split between Google Scholar (n= 40) and the ACM Digital Library (n=40). The author then used qualitative coding techniques, such as those outlined by Creswell and Poth1 and Saldana2, to code the data (i.e., the different sources). These initial codes, which functioned to sort and label the data, included: *music software, AI music recommendations, coding music, AI music productions, bias in tech, access and cost*, and *creativity*. These codes were then organized into an Excel spreadsheet, which allowed the author to identify key themes across the data. The key themes represented in the sources included in the dataset were as follows:

* 1. **Theme 1: Generative AI for Music Composition**

This theme was present in articles discussing how machine learning models generate original compositions. Because of how broad this theme was, it was then divided into two subthemes. Subtheme 1 included literature focusing on digital audio workstations (DAWs). The second subtheme, Subtheme 2, focused on contemporary coding platforms.

* 1. **Theme 2**: **Algorithmic Recommendations**

This theme encompassed literature focused on how AI is used to suggest songs to users and cultivate specific listening preferences and habits.

* 1. **Theme 3**: **Ethical Implications**

This theme combined the two subthemes of (1) accessibility concerns and (2) digital bias. It includes literature that explores the potential of AI in digital music creation as it offers possibilities for making the world a more just place, while at the same time acknowledging that it can also contribute to certain injustices.

In cases where a source addressed multiple themes, it was counted towards each relevant category. Sources that appeared in both databases were only counted once, ensuring that all duplicates were excluded. Sources that did not neatly fit into these themes were categorized as “Other,” and are not included in the discussion presented here. The frequency of each theme within the dataset is displayed in Figure 2.

A graph of different colored squares

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*Figure 2*: *Coding Results According to Theme*

1. **Discussion** 
   1. **Theme 1: Generative AI for Music Composition**

While the integration of computers and music may seem like a recent invention, the truth is that the two fields have been in collaboration with one another for several decades. In fact, as far back as 1951, Australia’s first digital computer, named Commonwealth Scientific and Industrial Research Automation Computer (CSIRAC), was the first computer to generate music3. A few years later, in 1957, the fields of music and computer science saw further integration with the emergence of the first computer to use algorithms for musical production, when the University of Illinois’ Lejaren Hiller and Leonard Isaacson created the “Illiac Suite.” This represented the first musical score to have been composed by a computer using a predefined set of rules (i.e., algorithms)4. Figure 1 below presented a timeline of digital music innovation for reference.

A screenshot of a graph

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*Figure 1: Timeline of Digital Music Innovation*

These initial explorations of how computer science could aid in musical production paved the way for the myriad applications available today. Now, with such advances, an entire orchestra of strings, woodwinds, percussion, and brass are offered within the confines of a digital audio workstation (DAW)—the focus of Subtheme 1.

* + 1. **Subtheme 1: Digital Audio Workstations (DAWs)**

A digital audio workstation (DAW) is “software designed to enable multitrack audio and MIDI [Musical Instrument Digital Interface] recording, editing and mixing on your computer”5. DAWs were heavily represented in the sources gathered for this review (n=24). Some of the DAWs more commonly referenced in the literature included programs like Ableton Live6, FL Studio7, and Logic Pro8, all of which use code to accomplish anything from recording multiple audio tracks to layering sounds, to implementing effects like echoes and pitch tuning. Many of the sources included described how these programs feature virtual instruments that use pre-recorded sounds that are prompted by MIDI notes.

The sources represented within this dataset also made distinctions between event-driven programming and procedural programming9. With this “event-driven programming” external data in the form of user input (i.e., a keypress) triggers a certain event10. An example of how event-triggered programming might be used in this context is where one presses a note on a MIDI controller (i.e., a MIDI note is received). The DAW then routes the event to a virtual instrument, which then produces a sound. In the case of some of the specific programs mentioned above, like FL Studio or Ableton, when one presses the middle note C, piano virtual studio technology (VST) plays the corresponding note.

Other sources described what may be classified as “procedural programming.” Rather than rely on external cues, procedural programming is based on a fixed series of events. Early applications of procedural programming for music composition, would draw upon elements of musical theory to establish rules that acted as parameters for the “raw material” to be generated within them11. For example, with procedural programming, tenets of musical theory that pertain to voice leading or chord progression could be written as a rule that acts a guardrail for the composition that follows. Kaushik looks at how the music used in video games is created using procedural programming methods that involve either automatic systems or an algorithm12. The author addresses how rule-based systems are used to adjust the player’s actions to the game’s environment. These methods allow the game designers to avoid using pre-recorded audio content, making the game more interactive and engaging for the user.

* + 1. **Subtheme 2: Coding Platforms**

Building off of the notion of creating music through a series of fixed rules, different coding platforms represented another way for creating music that was often cited in the literature. Yet, unlike DAWs, which allow users to generate music by clicking buttons or navigating menus, with coding platforms, users write code to make music happen. The code tells the computer what notes to play, how fast to play them, and what effects to use—like changing the pitch or adding an echo.

Two of the most commonly cited platforms in the dataset included the platforms Sonic Pi and Tidal Cycles. In Sonic Pi, users write commands in a programming language called Ruby to produce music. They can write loops to repeat sounds, change the pitch of a certain note, or accelerate or decelerate rhythms. Researchers like Aaron et al. compare how users in Sonic Pi write instructions in a step-by-step process that is similar to following a recipe13. They state, “The idea of a program is as a sequence of statements written in a programming language. Changing the order of the statements changes the behaviour of the program.”

The second often-cited platform within the literature was TidalCycles. Even though this particular program uses a different kind of code than Sonic Pi, the basic idea of using pieces of code to change music in real-time while it is playing remains the same. The Haskell programming language that TidalCycles is built on is especially popular for live-coding performances. Using tools like TidalCycles, users can continuously update the code to alter the music as it plays out14.

* + 1. **Theme 2: Algorithmic Recommendations**

Another large subset of the dataset touched on AI for algorithmic music recommendations. These articles addressed the capacity of AI to use deep learning to tailor new music offerings to users. These papers present AI as using deep learning——a process where AI is fed large amounts of data in order to start to identify patterns and key characteristics in that data15—to detect user preferences and recommend new music based on those preferences. Some of the more commonly referenced platforms that harness the power of AI to suggest new songs and deliver personalized playlists include Spotify, YouTube Music, and Apple Music.

But within the literature, digital technologies like AI are presented as doing much more than just recommending music; AI can also use algorithms to create music. Open AI’s MuseNet, Google’s Magenta program, and AIVA were all platforms that were introduced for using AI-driven digital technologies to compose songs, or parts of songs like melodies, according to a specific style or genre using neural networks that learn by example. A spectrum of human-computer collaboration is presented in Figure 3 below.

A screenshot of a computer

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*Figure 3: Human-AI Music Collaboration Spectrum.*

In their article, “Music Generation by Deep Learning—Challenges and Directions,” Briot and Pachet explore how deep learning allows AI to imitate styles of other songs to generate its own sequences of music16. This imitation, however, represents one of the greatest critiques of computer-assisted music production: a lack of creativity17. The authors argue that in training the AI on preexisting musical data, the result may come across as unoriginal. To address this issue, they suggest a system that invites greater user control and customization. The new system the authors envision would be much more interactive, which would, ideally, avoid some of the pitfalls of AI in music production, such as the lack of creativity mentioned previously.

Fiebrink and Caramiaux argue for something similar18. In looking at how machine learning algorithms can be used to create music, the researchers assert that these tools would be more appropriately regarded as *partners* in the creative music-making process. By emphasizing the need for user-centered design that is responsive to user input, human-computer interactions can lead to more creative collaborations between musicians and these machines. The authors also highlight that machine learning systems should be adaptable and flexible, in addition to collaborative. They should respond to and account for different musical contexts, as well as the objectives of the musician/user, instead of forcing the musical production to fit predefined workflows.

* 1. **Theme 3: Ethical Implications**
     1. **Subtheme 1: Accessibility Concerns**

The third theme that appeared across the literature took on an ethical component. Many researchers, such as Pedrini et al., acknowledge that several of the DAWs and coding platforms mentioned above make musical production technologies accessible by offering users an affordable solution that does not require expensive equipment19. In fact, with these digital technologies, an aspiring artist can create the sounds produced by an entire orchestra for the price of a laptop and DAW subscription (which ranges from anywhere from $99 to $800). Therefore, whereas previously, musical production was only open to people with extensive financial means, now, with innovations in digital technologies, users of various income levels can participate in music production20.

The articles included in this dataset also considered accessibility in terms of users’ abilities. People with various mobility issues may experience difficulty in playing the piano or strumming a guitar. However, some scholars argue that the technologies described in this article make musical production accessible to these individuals, as all they have to do is click a button or press a mouse. It is worth pointing out, though, that these technologies may not be user-friendly for all abilities. Pedrini et al.noted that DAWs such as AvidPro tools, Cockos, and REAPER may present accessibility concerns for blind and visually impaired people19.

The theme of ethical debates related to the accessibility of these technologies also included a concern for the technology gap, often referred to as the “Digital Divide.” While more and more places throughout the globe are gaining access to technology through improved infrastructure, many places are still without reliable internet services. Additionally, the cost of software and hardware may still be too high for some. That is why scholars like Yfantis et al. argue that digital musical production is still subject to accessibility concerns in terms of costs and technology access21.

* + 1. **Subtheme 2: Digital Equity and Bias**

Finally, the last ethical consideration that appeared in the dataset addresses cultural biases in digital music algorithm-based recommendations. In his book, *Computing Taste: Algorithms and the Makers of Music Recommendations*, cultural anthropologist Nick Seaver argues that algorithm-based recommendation systems are teaching listeners to hear music in a way that is specifically North American22. Similarly, Kowald et al. study of a dataset of AI-recommended music from Last.fm found that recommended songs tended to also be the popular ones, which opens the door for issues of inclusivity and diversity in digital music production23. Algorithm-based musical recommendations can work towards reducing cultural biases that favor Western preferences and mainstream genres, however, by looking to a user’s social network for recommendations. Instead of a “top down” approach to music recommendations, Furini and Fragnelli suggest tapping into what a user’s friends are listening to. This may provide recommendations in a more organic way that also reduces biases regarding mainstream music preferences.

1. **Conclusion: Towards a Collaborative Computing Model**

In summary, this review of the literature on digital music production presented several key themes characterizing leading research in the fields of music and computer science. The first theme that came up focused on digital audio workstations (DAWs), the second on algorithm-based recommendations for music delivery, and the third on ethical debates within the realm of digital music production. Each of these themes offer key takeaways worthy of further consideration as musicians and computer scientists aim to create future interdisciplinary collaborations. In fact, greater collaboration between humans and computers was identified as a need by several of the authors featured in this dataset. These scholars recommended refining the design of DAWs and coding platforms to make them more interactive and less constrained by predefined workflows. By giving users more freedom in their productions, these collaborative elements could also result in greater creativity in the content they generate, which would alleviate concerns about AI-assisted musical production lacking creativity.

Accessibility and inclusivity were also important points raised in the literature. Several scholars noted that computer-assisted musical production allowed for people of all abilities and income levels to participate, whereas others pointed out that users with visual impairments might be excluded, as well as those who live in areas without adequate technological infrastructure. Researchers also highlighted the biases that exist within AI-informed recommendation systems that can push users to listen to music that reflects mainstream media and Western culture. These systems can therefore exclude emerging or less popular artists, and those who come from cultures outside of North America and Europe.

As findings from this literature review suggest, the use of digital technology for musical composition and delivery represents a double-edged sword. Since computer science is a relatively young field, challenges and pitfalls are to be expected. However, in seeking to bring greater awareness to both the promise and perils of digital technologies when used for music, this review may pave the way for more interactive hybrid systems that capitalize on the strengths of digital technologies and integrate them with human creativity. Future innovations in this field would therefore not be entirely manmade or completely machine but combine the best of both.

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