Ethicality of AI Using Copyrighted Music for Music Generation

In the last couple of years Artificial Intelligence (AI) of all forms have taken over our daily lives and how we complete tasks. AI in the simplest terms are machines or software's that are created to complete tasks that require human intelligence. A Large Language Model (LLM), which is a branch of AI that takes in and produces human language such as ChatGPT or Gemini and can form answers in seconds. They can do things like revise this paper, make code to solve a problem, and much more. New forms of AI are constantly emerging and getting better including Generative Artificial Intelligence (GenAI) that can create things such as images, videos, and music in a short amount of time. These new technologies have given rise to debates over the use of data to train these models including concerns of privacy, consent, and copyrighted materials. One of the debates is in the GenAI area specifically with music generation and what data the AI should be able to use considering the perspectives of the artists, consumers, and the companies that create these new forms of AI. Artists may not want their music to be used by AI to be used to create new music, however consumers could want as much music as possible so that the GenAI can create tailored music to the best of its ability. The companies need to balance staying out of legal troubles, while also giving their users the best software they can. This paper will explore the details of how these new music generation GenAI models work, current public perceptions of the technology, and case studies that involve the legal and ethical challenges to these new systems. The central topic I will examine is whether AI music generation technologies should be permitted to utilize copyrighted music in training data, looking at how the models work, the benefits and perceptions of the technology, and the ethical and legal challenges for both the music artists and GenAI companies.

To fully understand this ethical debate, we must have a firm understanding of how these AI models work specifically in the music generation field to know the implications of the model training on the copyrighted material. AI models are trained on data from various places such as the internet and databases, using the data to answer the users prompts. Leading experts in AI training from around the country put it as easy as the "generation process usually consists of two steps: extracting intent information from human instructions and generating content according to the extracted intentions" (Cao et al., 2025, p. 2). We can now start to see how these models operate by figuring out what it is meant to do and then generating a response off that. To dive deeper into these models lets go step by step starting with the algorithms in the background used to sift through the user input. Known as a transformer, it is explained that "Transformer architecture is mainly based on a self-attention mechanism that allows the model to attend to different parts in an input sequence" (Cao et al., 2025, p. 5). From this, we can see how these software's such as ChatGPT can take in our text and know what we are asking it. The transformer described above will assign more weight to important words and phrases and less weight to words that do not change the meaning of the output that much. This process is part of the encoding process of the model where it takes in input and searches its dataset for possible solutions. Once the decoder gets data from the encoder, in GenAI contexts it begins to put together content that the user wants. In a similar model to music generation, text to audio GenAI has improved from "speech recognition and synthesis…[to] the introduction of deep neural networks [as] a significant turning point" (Cao et al., 2025, p. 17). These new processes of neural networks have allowed the AI to make better decisions and create better audio in response to text input. This includes translating to other languages as well as cutting out any noise in the audio track. These neural networks work by having nodes and connections each with a different weight that allows the model to make the best decisions as possible. Now that we have learned about other models, let's investigate the specifics of music generation models. These systems usually take in user text or recommendations on what to create and outputs audio or music that the AI creates from audio in their dataset. The main properties of these models are making sure that they can generate music that is coherent and able to take user input and turn it into specific music to what the consumer wants. There are two types of audio files in the training data called symbolic audio or raw audio files. Symbolic audio is known as "encoding music information through symbols that represent different aspects of music. The most common form of symbolic music data is MIDI (Music Instrument Digital Interface) which uses discrete values to represent the note pitches and their duration" (Yunoki et al., 2023, p. 103). MIDIs are very common in the music industry for communicated certain notes or sounds from an instrument to be processed by a computer program. For example, you can connect some musical keyboards to a laptop and use a MIDI do get the key input translated into discrete symbols to be processed and edited by a program on the computer. On the other hand, "Raw audio refers to any music file format which encodes an actual audio signal. Such file formats include MP3 files, .WAV files, .FLAC files, and others, which can be used for training algorithms" (Yunoki et al., 2023, p.103). This type of audio is continuous meaning there are no gaps in the data compared to the discrete data of symbolic audio that only collects data every so often. This can be better for music generation; however, it takes more computational power and complexity compared to discrete data. Like other models mentioned, AI music generation also mainly takes place using a transformer architecture to generate the best response based on the given input. These transformers are not only getting better at predictions but also are getting more efficient with some "reducing $O(n^2)$ time and memory costs to $O(n \sqrt{n})$" (Yunoki et al., 2023, p. 107). These reductions allow the models to generate responses quicker while also using less energy in the process. While the model is working behind the scenes it also has genre categories or tags on the data. A study done on the four most popular music genre classification algorithms with various neural network structures found that the Random Forest algorithm was the most accurate. The model's "ensemble of decision trees allowed it to capture complex relationships in the data more effectively than the other models" (Mogonediwa, 2024, p. 5). Decision trees are utilized by most AI models to make decisions and are useful for classifications like this. The models can also "include platforms that allow users to select various parameters such as mood, genre, or activity as the guiding elements for music generation" (Zhu et al., 2023, p. 31). Now that we can see all that these models have the capability of doing and how these processes work, let's explore the companies that uses these models. Some of the companies use "machine learning to create what is variously referred to as production or library music" (Drott, 2021, p. 193). This music is used in the background of things like games or advertisements and is not used directly for user consumption. However, there is a second type of company that targets users by making personalized requests of current songs or using the current song data library to create new songs. Either way, all these companies are using data from all over the web and other sources. This new ecosystem "of commercial music AI doesn't involve one group of users being connected to another, but instead a group of users being connected to an AI system" (Drott, 2021, p. 196). Knowing this shows how it is hard to just blame one group when so many companies are connected to the GenAI models. This along with unclear laws makes it hard to place blame or press charges on companies for using copyrighted data. Since we now understand what goes into these models and how they work, we can investigate the uses and public perceptions of these new technologies.

These models can create music tailored to user needs and cultural details that are not captured in traditional music, raising public opinions on this new technology. One of the big ways that these systems can help users the most is through emotional or affective music generation. To think about this, we must first remind ourselves that “music is often used as a powerful medium for inducing and mediating the mood and emotional state of the listener” (Dash & Agres, 2024, p. 1). Think about times in your own life where music has made a difference in your mood towards a situation. Some of the things that these systems can do include “the ability to skirt copyright issues, the computational means of blending genres/musical elements in novel ways, and, in the case of real time music generation systems, the ability to flexibly tailor the generated music to aspects of the environment or changes in the listeners’ physical or emotional state” (Dash & Agres, 2024, p. 2). This describes how some of the models do not always have to worry about copyright issues because they generate new and unique music with new features. Models like these are being used in many contexts including the healthcare to create soothing music for patients and in virtual reality to create a more immersive experience. This type of affective music generation (AMG) uses a similar, but more complex methodology than typical AI methods. Here is a list of the steps used, “The TEI [Target Emotion Identification] component takes input from the user or input device and maps it to the emotion domain in a representation usable by the system. The AMG component then uses the emotion information provided by the TEI component and composes affective music accordingly. Lastly, the affective musical outputs (e.g., pieces or excerpts of music) are evaluated by the EE [Emotion Evaluation] component (which can involve both computational and human evaluation) to examine their emotional expressiveness” (Dash &. Agres, 2024, p. 5). The two-part emotional examination allows the models to double check the music to ensure that it aligns better with what the user asked for. As an argument for the positive effects of music on mental and physical health, “there is a direct correlation between the reported negativity of a musical piece, the user’s GSR [Galvanic Skin Response] readings and the emotions they describe feeling in a questionnaire survey conducted after listening” (Williams et al., 2020, p. 4). The GSR mentioned is a test that measures the conductivity of the skin which relates to human stress levels. This fact means that based on the music you are listening to it changes both your emotional state and stress levels. About AI music generation, it has been said that “it is important that we do not confuse the role of an ‘artist’ with that of an AI developer, and nor should we ‘blaspheme against’ the ‘traditional act of composition’ by calling a developer of music AI a ‘composer’” (Huang et al., 2022, p. 5). He is making it clear that the makers GenAI are not composers or artists, but that musicians are still the only composers. There is also a cultural aspect to this technology as most music produced today is the typical Western culture’s tastes without much notice to Eastern cultures. AI’s ability to relate to cultures “‘shines a light’ on cultural traditions and ‘causes this re-imagination and re-invigoration of the culture in a way that's very, very different’ to previous forms of technology” (Huang et al., 2022, p. 7). Explaining how these models can relate to cultures in ways that have never been done before with typical music. Also, we must remember that “Cultural differences play a profound role in shaping the technological characteristics of symbolic music generation. Eastern music differs notably from Western classical music” (Wang et al., 2024, p. 16). This is currently a challenge for some GenAI models that are trained on Western data, however they are constantly improving to be able to create music of all cultures. In the United States, perceptions of this AI enhanced music are rising with Millennials or older having 36% interest and Gen Z or younger having 49% interest (U.S: Interest in AI-enhanced music by generation, 2024). This shows how as a society we are becoming more allowable with AI to help us complete tasks. Now that we understand the models, have learned of some benefits and public perceptions, let's investigate legal and ethical cases that have happened relating to AI music generation.

Our focus will now be on the history of AI laws in the context of copyrighted material including cases against GenAI companies and possible solutions. One issue related to this are soundalikes that can be generated based on an inputted voice. One comment made about these technologies was that "These AI-generated soundalikes implicate artists' copyright protections and reputations throughout their lifetimes and after death" (Juzon, 2024, p. 2). This speaks to the implications that these soundalikes can cause and the stress upon the artists. We can start to see the dilemma in these models that they can have great benefits while also causing unwanted burdens to some of the people involved. To sum up the court debate, it has been said that "If courts hold that the use of copyrighted inputs constitutes infringement, there may be a chilling effect on AI music generation. Alternatively, if courts find that this use is not infringing, rights holders may lose control over their works and fail to receive compensation for the use of their works" (Juzon, 2024, p. 3). In response to this so far, the courts have not decided because either way it is hard to see a win-win situation for both sides. The current U.S. copyright law includes lots of parts of music including "The sound produced by a performer's rendition of a composition—how it is sung, played, or arranged" (Juzon, 2024, p. 7). Knowing that all of this can be copyrighted shows the murky territory of AI music generation in these areas. These laws also usually refer to actual products that are semi-permanent so there are questions if these AI generated songs would count since they are temporary and generated only once. Copyright holders are also entitled to anything that derives from their original copyrighted material. In music it includes "musical arrangements, sound recordings, or other modifications that create an original work of authorship" (Juzon, 2024, p. 7). This adds even more reason to why it can be easier to see that AI can do some of these things and could possibly be held accountable for this. The Digital Millenium Copyright Act (DMCA) defined standards on taking down the copyrighted material of others. In order "To obtain a DMCA takedown, a copyright holder must give notice to a third party that a work the third party is distributing is infringing the copyright" (Juzon, 2024, p. 12). This explains the process of removing copyrighted material if needed from a platform. Some proposed solutions to this ethical debate include "addressing legislative intent with the adaptive legal framework and robust metadata implementation in the AI model can lead to the proper protection of copyright laws" (Surbhi & Roy, 2024, p. 10). This means that with adjusting the current laws and implementing ways to check if the output of these models is copyrighted then copyrighted material can be better protected. Based off all this debate, let's investigate some case studies of GenAI music generation companies. One case involves Universal Music Group urging Apple Music and Spotify to block AI companies from training on copyrighted music. When talking about what AI can do with this material one person said "Much of generative AI is trained on popular music. You could say, I want to compose a song with Taylor Swift-like lyrics, Bruno Mars-style vocals, and have it sound like a Harry Styles song. The result you get is because the AI has been trained with the intellectual property [IP] of those artists" (ContentEngine LLC, 2023, p. 1). This exposes these companies for using the IP of artists sometimes without consent or financial compensation. Another case involves tech giant "Google [that] already has a service that generates music from text, MusicLM, trained with a dataset of 280,000 hours of music and that, for the moment, the company has not launched because of a 'risk of possible misappropriation of creative content'" (ContentEngine LLC, 2023, p. 1). It seems that Google understands the weight of using copyrighted material and are being cautious in releasing new software. Pozalabs is a South Korean AI music generation company that uses "over one million Musical Instrument Digital Interface (MIDI) sound samples and 50,000 vocal samples -- a dataset meticulously created by its 15 in-house professional composers" (Pozalabs Responds to SACEM, 2024, p. 1). This company does this to avoid any plagiarism issues or copyright infringements. This is an example of a GenAI company that does not use any external data, but only their own in house-built music. This company proposes another solution of the "development of artist-specific music generation models that could benefit AI technology and human artists" (Pozalabs Responds to SACEM, 2024, p. 2). This would be a specialized AI model made only on data from a certain artist and would allow them to be compensated for their music being used. Another example is that "Sony Music Group has issued warnings to over 700 tech companies and music streaming services, cautioning them against using its music to train AI systems without explicit permission" (Sony Music Warns 700 Companies, 2024, p. 1). They are doing this because they have vowed to protect their artists and are trying to intimidate AI companies to prevent their music from being used. We can see overall that the courts are currently very quiet on this issue, and it has mainly been companies asking other companies to not train on copyrighted data. Some possible solutions without erasing one side of the argument mentioned include compensation for the artists, consent when training on data, more companies that do not use external data, and smaller models specialized for a single artist so they can easily monitor data and get profits. Overall, these case studies allow us to see the current legal background on GenAI music generation systems and possible solutions.

Weighing the current legal state and public perceptions of these new GenAI music generation technologies as well as now understanding how these models work, we can make an informed decision on the future of these models in relation to copyrighted material. In review, the public views of this technology are increasing with younger generations and as AI becomes more popular. Benefits from these models are also becoming better as they can recommend more personalized songs than ever before based on users' needs. Companies that make the AI have increased amounts of data including access to copyrighted material. Finally, the current legal system has little to say about the new systems, but some solutions have been offered by companies including compensation and more models that only use internal data made by themselves. With all of this in mind it is safe to say that this debate is not going away and I would say neither are the AI companies or music artists. To answer our central question, I think it is a very murky legal question on whether this GenAI is supposed to train on copyrighted material. From the artists perspective they may not want their music to be trained. Due to all these factors, I think the best path forward for AI music generation technologies are to start including some of my solutions from above into their business model. That includes asking musicians for consent, companies using their own created data, and artist compensation including by creating smaller models to more easily track how often each artists music is being used. These solutions will create the best path forward by not dismantling GenAI companies but allowing them to operate under a more ethically sound framework. To fully understand this question better, more research could be done into both the effects of creating an AI law and case studies into companies that have begun to implement these solutions. In response to this, us as users can change the way we view all AI. We can be more conscientious of the data that is going into the model and what restrictions the company has on the data. In doing this we can shape our own ethical decision making by choosing companies based on what data they allow and do not allow into their model. Overall, artists, AI companies, and the public should be aware of this ongoing debate and take measures to find a middle ground for everyone involved.

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