Artificial Intelligence in the Modern Music Industry: The Cases of Digital Distribution and Creation

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LAS Major Arts & Humanities: Past-Present-Future

Date of Submission: 30/10/2024

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Abstract

As is the case with many areas of daily life, artificial intelligence is currently transforming the modern music industry, particularly influencing digital distribution and creation. Current research deals with both the technical specificities of AI technology as well as the broader integration of AI in the music industry as a whole. The amount of interdisciplinary research with a holistic view that also encompasses ethical implications or future perspectives is growing. Thus, this paper honors this scope through a comprehensive analysis of AI's role in music distribution, including recommender systems and creation, focusing on generative and descriptive AI tools that assist the production process. Using a systematic review methodology, the study examines the state of current research and discusses two case examples of AI in digital music distribution and creation. Besides exploring how AI is used in the music industry's commercial and creative paradigms, the research also shows that these innovations have stakeholders facing various ethical, legal, or economic challenges going forward.

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1 Introduction

Music creation and its distribution went from purely acoustic sound and traditional ways of passing on art to the first instruments and music notation, to the assistance of synthesizers and vinyl stores, and through the emergence of digital audio workstations (DAWs) and mp3 downloads on the internet. The most recent development in how music is created, shared, and listened to is bedded in the all-encompassing predominance of digital music production and online streaming.

When discussing today's most novel technological achievements, in any branch where digitalization and human interaction play a vital role, artificial intelligence (AI) must be mentioned. AI has arrived, and it will probably never leave. This is no different in the field of music. The most significant change came about with the invention of the Internet and the possibility of storing and playing music via audio files. Baby boomers have witnessed these profound changes, while the current generation of digital natives might very well see the next great transformation within the music industry. People might be familiar with the use of algorithms on social media platforms or various other media services to create a personalized experience (Stammer, 2023). Through the news and other media outlets, one has undoubtedly at least heard of groundbreaking developments fueled by AI in engineering, medicine, finance, transportation, logistics, and countless other fields. The same applies to virtual reality products or thought experiments of an entirely virtual reality, such as the metaverse. Within the context of music distribution, creation, and consumption, however, the average listener might not necessarily be aware of the ways in which AI is already dominating all different facets of the music industry, aside from the current hype of AI-generated songs. This applies to streaming, production, performance, and all other fields. J. Heffler describes AI as "the next opportunity, a highly advanced and fast-evolving tool in a continuum" (Heffler, 2023). AI has great potential to enhance virtually all areas of human life, and music is no exception (Tillmann & Zaddach, 2024).

The integration of AI in digital processes always raises questions that can be understood as ambivalent, as a dichotomy. The controversy lies in the fact that AI can be understood as competing with human intelligence and work (Chow, 2023). Questions immediately arise in this context: Is AI a help or an obstacle? Does it enhance processes of creativity and productivity, or does it eliminate jobs? Is AI valuable or venomous? A blessing or a curse? The most apparent dichotomy lies within the necessary protection of the artist and their intellectual property juxtaposed with a constant motivation to stimulate innovation and secure a better human-machine relationship. This means that the creative human preferably needs to find ways to work *with* AI in every aspect of their life, not *against* it.

This paper strives to explore the state of the art of AI usage in the modern music industry by firstly examining what AI tools or AI-based techniques are used in the (digital) distribution and creation of music and through an explorative systematic literature review. After exploring this somewhat novel area of research, two case studies on (1) distribution and (2) creation situate the role of the identified AI applications in the music industry and deduce findings from the current state of literature. The conceptualization of AI usage in the music industry that will thereby be performed proves that AI is part of virtually every branch within contemporary music and that issues tied to its usage are of a pressing nature, mainly because it is often assumed that AI's integration foreshadows another paradigm shift within the creative industries (Lovett, 2024). Since there seems to be both a call and a lack of interdisciplinary research, this paper aims at synthesizing seemingly different application areas of AI. Furthermore, the paper will outline the potential challenges and opportunities of AI usage in the digital music sphere and then attempt to show the future implications and possible predictions. Ethical and legal considerations play a part within the field of music, with crucial AI ethics notions and insights that can be deducted from the research. Finally, this paper argues that all complex issues identified share the characteristic that they can somewhat be traced back to the consumer's needs. We also find that the integration of AI use, following a task-based definition approach that captures the broader practical understanding of what can be considered AI, steadily develops into the industry standard.

Understanding AI is of immense importance because multiple stakeholders are involved, and all of them must ideally benefit from its application. Stakeholders within the industry are experts or professionals, including but not limited to artists and DJs, music owners used as input for datasets of generative AI, AI programmers and service providers, label officials, and, since we are talking about intelligent machines, the machine itself (Tillmann & Zaddach, 2024). Current research is driven by the necessity to foster collaborative discourse in the future by integrating expertise from various fields such as data science, musicology, economics, and marketing (Braguinski, 2024). It is imperative to address the opportunities and challenges in academic discourse due to the swift evolution of technology. Practical guidance informing policy stakeholders is crucial for ensuring novel technology's fruitful and beneficial utilization and future innovation.

2 Key Terminology

2.1 Defining Artificial Intelligence

It is helpful to have some basic knowledge of what AI technology is prior to discussing what it is used for within the realm of music to provide a better fundamental understanding of the terminology this paper elaborates upon. Therefore, before making the connection to AI in music, let us examine some critically relevant and elemental considerations about definitions to form a better understanding of the bigger picture.

Defining AI is far from a trivial endeavor. To start, the most simplified definition is that the study of AI is "the science and engineering of making intelligent machines," which is how

Stanford professor John McCarthy first coined the term in 1955 (Manning, 2020). While the intuitive notion that it has something to do with a machine being able to perform tasks in a manner that is somewhat similar to the way humans approach problem-solving by using their own intelligence is certainly not wrong, finding a universally accepted definition of AI is hard. Not to say impossible. This is primarily due to the fact that it is used in many different fields and societies, and there are fundamentally different motivations regarding who uses it, programs it, and for what end it is used. One of the first terms that comes to mind when trying to define AI in its broadest sense is algorithm. AI does make use of algorithms and is closely related to this notion, but saying that AI is a type of algorithm is categorically incorrect. It needs to include many other aspects that make it AI. An algorithm can be understood as a specific instruction applied to a problem or calculation in order to solve it (Sheikh et al., 2023). Following this logic, the missing piece is that AI is capable of executing problem-solving in a way that displays the possession of human-like intelligence or that it at least imitates intelligence mutually understood to be inherent to humans. This is deemed as the strictest definition of AI. Here, hardcore purists would argue that current AI technology is too simple and unsophisticated even to be attributed with the capability of having something similar to human intelligence. This would lead to the issue of not only postulating a definition for a concept that does not exist yet but also attributing a human feature to a machine that we also do not understand fully yet, namely, intelligence. While this is undoubtedly true, thinking of AI in this way still provides the necessary preliminary understanding of what it is, so even though vastly indeterminate, the definition holds plenty of conceptual value. For the sake of simplicity, we will refrain from going further into a philosophical debate about what kind of definition is the *most* correct and look at a more operational perspective, which is using the scope of a tasked-based definition (Ibid.). After establishing common ground on a task-based understanding of AI, key terminology needs to be discussed to aid in fathoming AI operations in the context of music.

A task-based definition elaborates on the fact that AI is a technology that can imitate complex human skills in a context-dependent situation. The elaboration lies in identifying what complex human skills are meant specifically since the wording would otherwise be too vague. Of course, task-based definitions would still hold limitations, but that does not diminish their usefulness in a broader academic context when trying to grasp AI's societal value within a specific field of interest, such as the music business. Further explaining the tasks an AI technology can solve is particularly useful because it honors the embeddedness in the corresponding environment in which it is used and emphasizes what socioeconomic dynamics are influenced by its presence or vice versa. For this reason, this paper extracts ways to identify AI use not on technical or philosophical demarcation but on whether the task at hand is solved in its context.

The European Commission's High-Level Expert Group on Artificial Intelligence issued a suitable definition of AI technology. The expert group describes types of AI technology as "systems that display intelligent behavior by analyzing their environment and taking actions — with some degree of autonomy — to achieve specific goals" (HLEG, 2020). Here, one could argue the broadness of the definition by pointing out that this would also include machines or digital tools that do not qualify as AI, such as an air conditioner that automatically adjusts temperature output depending on the environment. For this reason, the notion of autonomy and its degree needs further assessment by verification in relation to the stakeholders that enable it, produce or utilize the technology, or restrict said autonomy while consulting AI technology to reach their goals.

What do we mean by autonomy in the context of artificial intelligence? First, it needs to be clarified that when talking about what constitutes an autonomous system, we do not (always) mean the principle of self-governance, as might be the case in politics, biology, or ethics (Manning, 2020). Instead, what is meant by attributing the capacity of certain degrees of autonomy to a machine is that the machine exhibits the ability to independently plan, navigate, and, most importantly, decide what steps it should take to achieve a task-specific goal with profoundly limited or no human intervention. In simple terms, this means that while an autonomous system still has to be initially programmed, it needs little to no human micromanagement or does not depend on it altogether, unlike a non-AI machine. Ergo, the lower the degree of human intervention in the decision-making process, the higher the degree of autonomy of the respective system. Thus, the only human intervention needed for an AI system's beneficial assistance would be input in the form of code, data, or commands. From this, it follows that the degree of autonomy in AI technology directly impacts whether an ordinary person observer would judge it to imitate human-like intelligence (or not). Correspondingly, whether a machine can be called AI radically depends on whether the machine 'deserves' the status with respect to what the current science deems to be a complex form of intelligence (Sheikh et al., 2023). Tied to this is the legitimate gatekeeping plea that the notion of intelligence is inherent to living beings and is misleading when used for machines. This also means that with the continuous development of science and the understanding of what intelligence is in general, the expectations we have of the problem-solving abilities of computers steadily rise simultaneously. This is primarily due to the fast pace at which both technology and human intelligence evolve, inevitably rendering outdated technology obsolete and repeatedly replacing it. It is safe to assume that, with great probability, definitions of AI will change and get more refined as time goes on with the present momentum of the public discourse.

2.2 Key Concepts of Artificial Intelligence in Music

Because the paper will discuss AI in a specific area, namely, the music industry, this paragraph strives to provide a brief overview of terminology that will be used multiple times without further elaboration in the subsequent sections. Explaining some terms beforehand provides better clarity. Since the concepts of autonomous systems and algorithms have already been touched upon, we will zoom in on weak and strong AI, machine and deep learning, neural networks, language processing, recommender systems, and filtering, the difference between generative and reactive (analytical) AI, and lastly, Web3.0 and Blockchain.

2.2.1 Weak and Strong AI

Firstly, a fundamental aspect of AI is the distinction between AI in the narrow or weak sense and AI in the general or strong sense. However, this differentiation is abstract and should not be applied to comparing two different types of AI in a practical sense. Instead, artificial general intelligence (AGI) can be interpreted as being a theoretical definite goal to reach in the development of AI technology.

When speaking of general or strong AI, we mean a future complete version of computational systems that function, learn, recognize, and solve complex tasks entirely independently to a level that mimics authentic intelligence with an uncanny resemblance to human cognition. Whether this is possibly attainable remains unanswered. Likewise, whether this should be achieved at all raises a plethora of exceedingly moral questions. In practice, AGI is a vision that is yet to be achieved, and every AI technology nowadays is dubbed weak or narrow AI (Sheikh et al., 2023). The main reason for this categorization is that current AI technology is programmed and consulted solely to solve or to aid in solving specific tasks. It goes without further explanation that this is nowhere near the most minimalist requirements of what would count as human cognition.

2.2.2 Machine Learning

Secondly, assuming that a human being needs to train and make experiences in order to recognize patterns and identify problem-solving solutions to apply in reaching a particular goal, computer systems that are deemed AI are developed and function based on what is called machine learning (ML). Through machine learning, the computer can learn and make informed decisions based on data. ML is the main component on which AI is based and, therefore, part of every AI tool; it goes without saying that this is no different for intelligent computer systems used in every digitalized aspect of music. From practical applications in music streaming services like Spotify, Soundcloud, or Apple Music to analyze user preferences to using ML algorithms in identifying patterns or themes in music notation for data-gathering processes, machine learning is used in many instances (Braguinski, 2024). The same principle applies to having a computer system learn from a dataset to aid in the production process of music composition.

The most prominent type of ML in recent times is deep learning. Deep learning utilizes neural networks with multiple layers to operate with large and complex datasets (Liu et al., 2017). This increases accuracy and pace, ultimately enhancing all processes in which it is applied. The improvement of deep learning and the utilization of neural networks made top streaming services or AI production tools better market competitors within the music industry (Elbir, 2020). Furthermore, great long-term and short-term advancements can be achieved in musicological research. In the short-term, comprehending and interpreting sophisticated corpora of music in history or direct generation of sound and possible AI music notation already surpasses what is humanly possible in workload and pace. In the long run, AI tools can possibly learn listening behavior, and fully automated pipelines can be created to produce music or standardize findings in musicology (Braguinski, 2024).

2.2.3 Neural Networks

In addition to what has been outlined above, neural networks used in deep learning can "compute with continuous (real number) representations, a little like the hierarchically organized human brains" (Manning, 2020). Although there are multiple types of neural networks, we can distinguish between two types that are of the highest relevance for AI in music: convolutional neural networks (CNNs) and recurrent neural networks (RNNs).

CNNs are deemed most effective in processing grid-like data structures such as images (Sumbati, 2024). Stakeholders of the music industry use CNN-driven systems for signal processing and music genre classification through analyzation of acoustic properties (Chamola et al., 2021; Murindanyi, 2024).

Recurrent Neural Networks (RNNs) are a type of neural network specially designed for processing sequential data. This makes them particularly well-suited for working with music, as music can be viewed as a series of notes and sounds unfolding over time (Reddy, 2024). Learning these music sequences is valuable for tasks such as genre classification and digital music composition, as it enables the generation of precise recommendations for users of streaming platforms and the creation of melodies that harmonize with specific musical keys, harmonies, or rhythms (Rickard, 2022). Similar to how human creativity is often sparked through inspiration and imitation, the effectiveness of RNNs in music composition lies in their ability to quickly and accurately imitate musical styles (Gioti, 2021). One subtype of RNN is the Long Short-Term Memory network (LSTM), which consists of a cell, input gate, output gate, and forget gate working together to manage the flow of information within the network (Chang et al., 2019). This architecture allows for a thorough analysis of a large number of timestamps and the various states within the music sequence to detect patterns such as rhythm, harmony, and correlation to emotions triggered in the listener in multiple different genres and sub-genres.

2.2.4 Natural Language Processing

Natural language processing (NLP) refers to a computer system model in which text, searches, spoken word, or other forms of language input can be interpreted and learned to generate or provide a desired output. NLP is a fundamental and widespread model of computing used in search engines, ChatGPT, and a wide variety of other fields, such as plagiarism checks, spam filters, content analysis in social media, and many others. In the wake of swift innovations in deep learning within contemporary computer science, the tasks that NLP models can perform are growing in complexity. Computers are capable of understanding the meaning of human language better and better (Sheikh, 2023). As a matter of course, NLP plays a seminal role in AI usage in music. Keywords regarding production, genre, or semantic information in playlist curation are dataset inputs scanned through NLP and used by streaming providers such as Spotify, Apple Music, and, most probably, all other successful platforms (Goldmedia, 2024). NLP, therefore, postulates a fundamental basis for the most recent advances and developments in the AI tech field of any type.

2.2.5 Music Recommender Systems

Algorithmically powered recommender systems are integrated into any application that shows a user consumable (media) content or products on the internet. Be it video-sharing apps like YouTube or TikTok with recommender systems integrated into algorithmic personalized feeds, video streaming services like Netflix, or music streaming platforms such as Spotify or SoundCloud. Recommender systems aim to personalize the browsing experience by learning user behavior and suggesting (what the machine deems to be) relevant content. Large amounts of data are analyzed, and the system learns patterns to predict then what the respective user might prefer. The data encompasses browsing, purchasing, watching, or listening history, as well as activity on other apps. AI-powered recommendation systems can identify patterns and trends through the algorithm, enabling highly accurate predictions about similar content and future preferences (Hesmondhalgh et al., 2023).

In the context of music, recommender systems must be able to differentiate within the data they operate with, specifically, the type of songs. Therefore, genre classification is the most significant component in recommending songs on music streaming services (Murindanyi et al., 2024). Without learning how a song is categorized according to its acoustic properties and song metadata, preferences cannot be identified. Likewise, suggestions cannot be made appropriately. Genres are the most essential classification made within modern music. AI music recommender systems' machine learning techniques and neural networks are programmed to identify and precisely classify music in different genres to maximize efficiency in suggesting content to various consumer target groups. Modern (music) recommender systems use what is called hybrid filtering models in their operations. This will briefly be explained.

Two types of filtering are relevant to music recommender systems, which are used in unison, hence the term hybrid filter models (Schedl et al., 2015): the more straightforward type is collaborative filtering (CF) (Jannach et al., 2018), whereas the more recent and detailed type is referred to as content-based filtering (CBF). The former can be described as models that, for example, analyze what artists different users listen to, how long and how frequently this happens, or what songs are skipped to suggest songs by a particular artist to other users. Because similarity of content consumption plays a significant role here, the most used algorithmic feature here is K-Nearest Neighbors- (KNN) based collaborative filtering. Basic CF was developed as early as 1995, with music being one of the first application fields of CF (ibid., 2018). The latter refers to a filtering process tied to music information retrieval (MIR); that is, it focuses on extracting different forms of semantic information within music, such as audio signals or artist and album names (Schedl et al., 2015). As the name content-based filtering already suggests, contrary to CF, it is concerned with analyzing feature vectors and digitally tangible properties of the music itself. A third type of filtering, context-based filtering, helps extract data relating to mood or activity while listening to specific genres or songs.

Modern recommender systems, especially those used in the music field by Spotify, Apple Music, and co., use a hybrid of all the filtering types mentioned above coupled with deep learning techniques to ensure the highest degree of functionality and accuracy. Some examples of music recommendation-driven app features, such as self-generated playlists, include Spotify’s "Discover Weekly" and SoundCloud’s "Daily Drops," or simply the options of browsing feeds of recently uploaded music. SoundCloud provides a unique on-the-spot generated playlist feature called "Track Station," which gives the user a playlist of similar songs with any chosen song as its starting point. Since September 2024, SoundCloud integrated a feature for users to filter their liked songs by "dancy," "euphoric," "playful," or "optimistic," among other options.

2.2.6 Reactive and Generative AI in Music

While the aforementioned AI applications in music recommender systems are considered reactive AI, generative AI is a more recent type of AI. The main difference between the two is that reactive (sometimes called analytical or descriptive) AI does not create an output in the form of "new data" but provides outputs of existing data, learning from other existing data as input and applying rigid rules given to the systems for their tasks (Goldmedia, 2024). Generative AI, on the other hand, is trained with inputs of big data from which it learns. It can recognize patterns through its neural networks not only in a more sophisticated way, but the input learned can also be significantly sizable in quantity. Then, a generative AI system can create new data, which in the context of music production are synths, melodies, vocals, or even entire songs as a whole.

Because generative AI is becoming more and more advanced by the day, its role in the music industry merits impactful possibility but also controversy and important legal or moral questions regarding musical creativity and copyright (Novikova, 2024; Tillmann & Zaddach, 2024). When FlowGPT, an artist that publishes AI-generated songs, made a Daddy Yankee, Justin Bieber, and Bad Bunny collaboration hit that went immensely viral on TikTok, fans of all three artists loved the song, while Bad Bunny disliked it and discouraged fans from supporting AI-generated music. Reproducing, particularly the deep-faking of art, raises important questions and sheds light on urgent issues primarily of an ethical nature (Chow, 2023). More recent examples include the use of generative AI in Kanye "Ye" West's newest album publications, Vultures I and II. Another example is an underground AI SoundCloud artist called Moving in Silence, AI generating "Huncho Jack 2 (AI)", an entire deep-fake (Anantrasirichai & Bull, 2021) album, mimicking not only the production style of the instrumentals of the actual "Huncho Jack" album but also realistically replicating the voices of rap artists Travis Scott and Quavo. The AI artist's motivation was that fans of their supergroup duo project of the same name, Huncho Jack, have been awaiting a second album for many years.

2.2.7 Web3.0 & Blockchain Technology

Currently, the internet, as it is used today, is referred to as Web2.0. Web2.0 is largely controlled and dominated by high-revenue tech companies that hold user data and are able to monetize this data. Contrary to this, Web3.0 constitutes (a vision of) the future of the Internet as we know it today. Ethereum co-founder Gavin Wood coined the term in 2014. Following this, in 2021, the topic gained momentum in cryptocurrency circles, venture capital firms, and tech companies in the wake of the AI and crypto boom. The main difference compared to Web2.0 is that instead of giving up a significant portion of control, and with this, ownership rights that the user has over their own data, Web3.0 is run on decentralization with token-based transactions and data secured with blockchain technology. Blockchain technology is a form of ledger that is widely distributed on different digitally encrypted blocks worldwide (Naikwadi et al., 2020). This recording of transactions across a network ensures higher transparency, cyber security, scalability, and privacy beyond what the Web2.0 infrastructure can deliver. Therefore, Web3.0 is a future vision of a solution to the over-centralized internet. The current academic discourse is centered around exploring the technology's benefits and potential pitfalls (Monrat et al., 2019).

While many experts currently discuss advances in healthcare or innovation in tech, blockchain technology implementations and the Web3.0 infrastructure yield promising advancements regarding ownership through reforming the way in which royalties are paid and the way in which artists give away copyrights, at least partly, to other parties (O'Dair, 2017). This can be done by, for example, saving a song as a non-fungible token (NFT) on a blockchain as a unique asset with transparent and rigid ownership (O'Dair, 2019a). This works through so-called smart contracts that are encoded and attached to the NFTs on a blockchain (Simić et al., 2021) and enable secure payment transactions directly to the creator. Democratization through transparency and listener-to-artist connection proved especially important, as this paper will demonstrate later. One practical example of the application of blockchain technology or advances in the Web3.0 transformation in the music industry is the former pioneer of modern music distribution, Napster, which, by acquiring Mint Songs, a music NFT marketplace platform, is looking to strike a comeback in the globalized digital music distribution market (Strack, 2023; Dalugdug, 2023).

Another example is the decentralized music streaming platform Audius, which launched in 2019 (Audius Dashboard, 2024). As outlined above, Audius works with its own native cryptocurrency token, $AUDIO, to let artists distribute their music directly to fans without having labels or other third parties interfere (Rumburg et al., 2020).

3 Methods

To identify the most relevant literature regarding the topic of this paper, multiple databases have been searched using various approaches to search strategy with inclusion and exclusion criteria of key terms and concepts. Specific data has been extracted from the literature to answer this paper's research questions, which are:

- RQ1: What AI tools are used in digital music distribution and creation?
- RQ2: How did the academic research develop over time?
- RQ3: How is AI situated in the state of the industry?
- RQ4: What are the possible challenges, ethical implications, and future perspectives in research and the practical integration of AI in music?

Familiarization with the topic

To start the literature search and set the stage, simple Google searches on "digitalization of the music industry" or "how did AI affect the music industry?" were conducted. After getting a preliminary idea of where AI is situated in the timeline and discourse of music, it became clear that research and media information predominantly refer to what stakeholders use AI and how this changes the industrial complex of modern music. Multiple search prompts on ChatGPT were used to understand the basics of AI use by stakeholders. Some examples of these prompts are: "How did artificial intelligence influence music streaming?", "what is democratization of music?", "What is blockchain technology in simple terms, and how does it affect the music industry in the future?", "Will AI be good for the music industry?" and "What are some examples of artificial intelligence tools used in electronic music production?".

The twofold thematic structure of this paper has been established due to repeatedly encountering the importance of the interaction between stakeholders and their inseparable relationships. After consulting insider media pages, YouTube, Reddit, and (industry) reports, as well as company research on the topic, this assumption was confirmed because AI is used by all significant stakeholders in the industry. With that, exploring the topic and covering the entirety of AI usage by different stakeholders in the context of technological innovation in the overall music industry is better ensured by conducting two separate searches and data extractions, namely, one on the distribution and another on the creation of music. Visual and auditory media records included YouTube videos, insider podcasts, or shows such as "The Playlist" on Netflix. These amounted to 15 different records. Adding to this, 61 different webpages and non-scientific articles, such as news reports or blog posts that guided the following literature search and establishment of inclusion and exclusion criteria in terms of content, were consulted.

Database search & key term establishment

The databases searched were Google Scholar, IEEE Explore, WorldCat, and SpringerNature Link. Firstly, a broad boolean search string was developed, including both themes:

(Music AND (Industry OR Production OR Composition OR Streaming)) AND ((Artificial Intelligence) OR "AI")

As mentioned above, the decision was then made that the search ought to be structured so that it combines the two key terms and their specific alternative terms in three different search operations, namely, literature concerning distribution, creation, and blockchain technology (because blockchain is a narrow and more novel field that is better studied by a separate, precise search). The two key terms around which all alternatives were centered around were music and artificial intelligence. Those were combined with the boolean operator AND and separately distinguished with the boolean operator OR.

In the search operation for music distribution and artificial intelligence, the specific alternatives for the music search term were:

- Music recommendation
- Music recommender systems
- Music streaming
- Genre classification
- Genre detection
- Playlist curation

To zoom in on specific streaming platforms searches were conducted in which this key term concept was replaced by "Spotify" or "SoundCloud".
This key term concept was then connected with the key term concept artificial intelligence using the boolean operator AND, and had a higher amount of more specific alternatives, including these:

- Neural Network
- Deep learning
- Machine learning
- Algorithm
- Collaborative filtering
- Context-based filtering
- Hybrid filtering
- LSTM

One possible string for the database search of the digital distribution theme looked as follows:

(Music AND (Recommendation OR Streaming OR Genre Classification)) AND ((Artificial Intelligence OR Machine Learning OR Neural Network OR Filtering OR Playlist Curation OR "LSTM") OR "AI")

Even though this string proved to be effective, combinations of all alternatives were used in separate searches on the databases mentioned because Google Scholar and IEEE would provide too many results. The results on the mentioned databases, when applying this search string, looked as follows:

- Google Scholar: 18.100 results.
- IEEE: 1.563 results.
- WorldCat: 664 results (articles only).
- SpringerNature Link: 2787 results.

For the second search operation regarding music creation and artificial intelligence, the first key term concept of music included these (specific) alternatives:

- Music production
- Music composition
- Music creation
- Music mastering

- Music generation

The second key term concept of artificial intelligence also included these specific alternatives:

- Generative AI
- Machine Learning
- LLM
- LSTM

The boolean search string of this search operation is:

(Music AND (Production OR Composition OR Creation OR Mastering OR Generat*)) AND ((Artificial Intelligence OR Generative AI OR Machine Learning OR "LLM" OR "LSTM") OR "AI")

The search string yielded the following results on the databases consulted for this paper:

- Google Scholar: 139.000 results.
- IEEE: 1.269 results.
- WorldCat: 36.100 results.
- SpringerNature Link: 34.765 results.

The blockchain technology search operation was conducted in a simpler manner with searches including "music and blockchain technology" (17.700 results on Google Scholar), "music and Web3.0" (514 results on Google Scholar), or other alternatives of the corresponding key term concepts such as music production or streaming.

Mostly due to the reason that in the search operations, we see a lot more results when applying these broad boolean search strings; all results were narrowed down through sorting by relevancy, applying the search filter of only searching results published in 2010-2024, and focussing primarily on the first five pages of search results. Most included studies were found by using repeated and separate smaller search strings, including only two of the (specific) alternatives for the key term concepts. Creative industry conferences, such as the 3rd Conference on AI Music Creativity (AIMC 2022), were consulted, which yielded critical results.

Inclusion and exclusion criteria

In evaluating the significance of key findings and concepts covered in the literature, the primary exclusion criteria that were prioritized centered on the recency and relevancy of publication. The full-text articles in the forms of essays, chapters, or scholarly articles were systemically screened in multiple steps that led to exclusion or inclusion, with first looking at the title, then the abstract, the conclusion, and lastly, the findings or the main body of an essay. Studies ultimately included passed the scrutiny of applying the following criteria:

- The articles were either in English or German (Stammer, 2023 and Ostermann et al., 2022 are the only included articles written in German).
- Articles published before 2010 were excluded as long as there was not enough relevant information concerning the historical development of AI use in the industry.
- The articles discussed digital distribution and creation computer programs in the scope of AI, meaning the authors defined them as AI or they show clear attributes of what is objectively considered AI under a task-based definition.
- The articles that dealt with highly technical computer science jargon and specific programming problems in their research were excluded.
- Additionally, the records included provided substantial information on AI's effect on stakeholders and consumers.
- The main research question and corresponding findings explicitly concerned the mentioned (specific) alternatives for the key terms music and AI, which qualified the article for inclusion
- The articles were excluded when the dominant theme did not hold enough crucial information concerning the state of the art of AI in the music industry as a whole.
- The articles had to be peer-reviewed and published in a reputable journal or be part of books by reputable editors within the research field.

Research conducted well before 2019 was often deemed to be inconsequential to this research because the possibility of it needing to be updated outweighs the necessity for inclusion. Given the emerging nature of research on artificial intelligence in music distribution, consumption, or production, the emphasis was on inclusivity rather than exclusivity. This approach encompassed broad, exploratory, and descriptive work while disregarding narrow, quantitative studies focused on deep computer science-related methods. Such studies did not align with the explorative approach required to capture the comprehensive landscape of this subject matter. The literature surrounding topics tailored solely for musicians seeking professional advancement was also excluded. The majority of the excluded literature did not focus on artificial intelligence or music or only briefly touched upon the subject within the context of other findings that are too narrow in scope. In the number of articles shown in Figure 1, articles concerning blockchain technology and future perspectives were included in the "distribution" theme. In contrast, articles that dealt more with the music industry and AI as a whole were included in the collection of the "creation" theme.

Screening and extraction of data

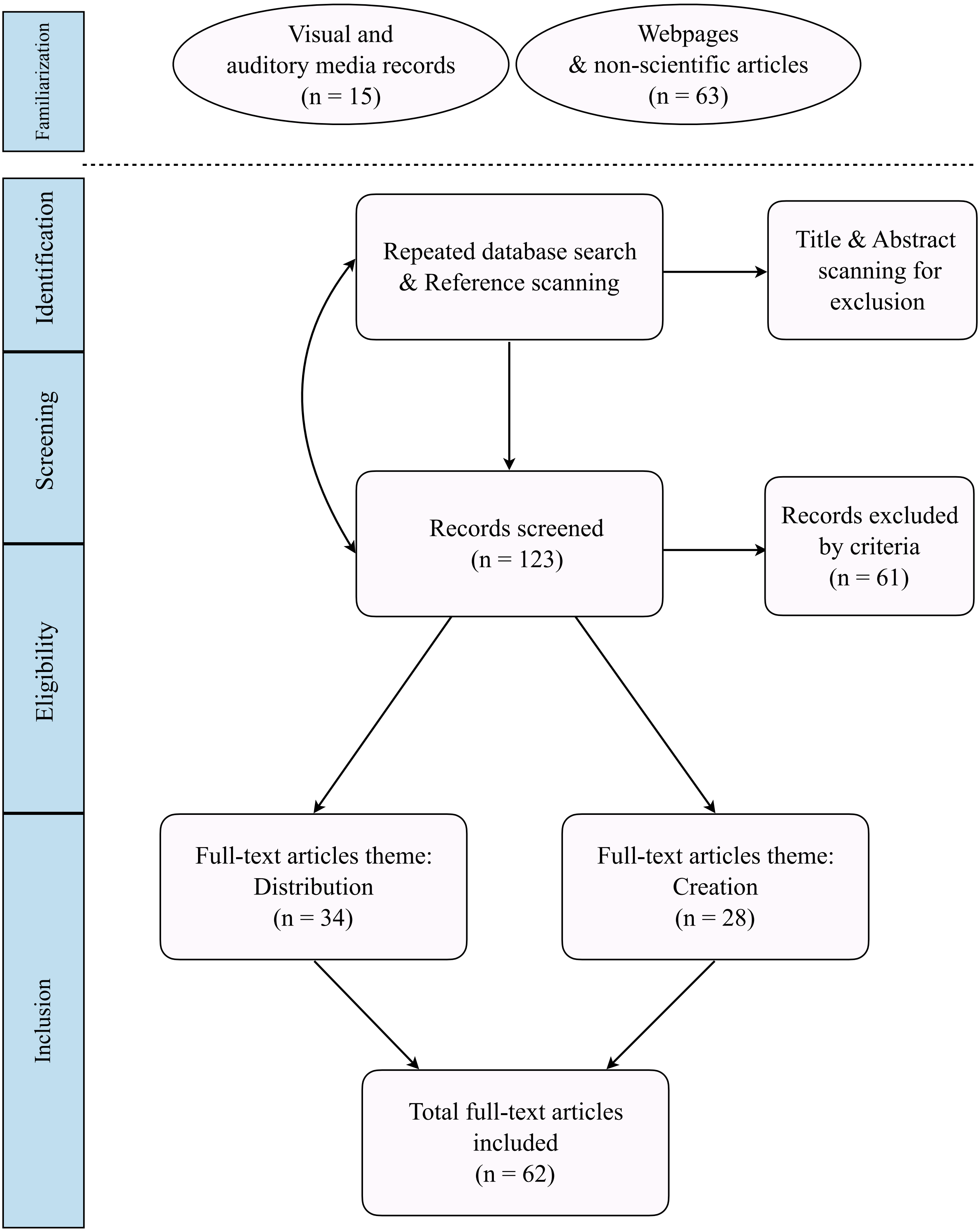

Fig. 1: Research process methodology.

Reference lists of records screened were scanned by looking at the titles in order to find articles that fit this paper's research questions. Records that passed the screening process ended up in the data extraction process. The articles were split into two main themes, depending on which theme was predominantly discussed in the source since the themes often overlapped and are not mutually exclusive. To extract the data, the articles were briefly summarized, the main findings were listed, and a theoretical framework was identified if possible.

Lastly, research gaps within the record or research gaps mentioned in the record concerning other research and corresponding implications for future research were extracted to then draft this paper's review. The AI-powered tool LitMaps has been used to deepen the search further, narrow the results down, and find articles that fit the research questions because of proximity in the scientific field within which the included articles operated.

Limitations

The limitations of this study revolve around two main issues that partly resemble limitations found in the comprehensive literature reviews of Hesmondhalgh, 2023 and Civit et al., 2022, whose studies served as nearest neighbor studies, greatly informing this paper's methodologies and scopes. The former performed a review on algorithmically-driven music recommendation systems and the latter conducted a systematic review on AI-based music generation. Hence, limitations having to do with the subject matter are encountered in other studies on the topic.

Firstly, the topic is evolving not only in academia or media discourse but also in the technological advancements it encompasses, which are in a stage of rapid progression as of the time of publication of this paper. This leads to the fact that the number of AI tools used in digital music distribution and creation is not only categorically indefinite but quantitively infinite. In addition to this, the challenges surrounding the implementation of AI in music accumulated at a fast pace, and new insights on these exponentially grow in relevancy as compared to older research on the topic. Deducing predictions and future perspectives from the current literature is necessary, but these can be largely imprecise due to the aforementioned circumstances.

4 Literature Review

AI is becoming a game-changing, transformative impetus in the digital processes of the music industry. This applies to a vast amount of processes within the fields of distribution, consumption, as well as the digitally driven creation of music. For this reason, synthesizing these different branches and merging their key findings together ultimately leaves us with a more profound and comprehensive holistic view of the modern music field as an industrial complex. Reviewing secondary literature will identify and describe what can be deemed the most insightful studies and academic sources on AI in the modern music industry. The search strategy used to find relevant sources is briefly mentioned. Subsequently, two main themes are examined, and lastly, the delivery of implications for future research and a synthesis of the research question of this paper will be performed by setting the stage of this paper by situating it within the plethora of current academic discourse. A critical analysis is implemented while summarizing the main themes. Discussing possible research gaps is part of these analyses. Therefore, the research stage and academic thought of the synergy of AI and the modern digital music sphere are explored and described. The direction of future research derived from the existing literature will be touched upon as well.

For the sake of clarity, the two themes that are mentioned above are (i) AI in music recommendation and (ii) AI in music production. By balancing the findings related to these diverse themes, the review aims to provide a comprehensive perspective on the integration of AI in today's music industry across various fields, including business and marketing, musical studies, and data or computer science, to secure a better understanding of the state of the art. This will improve the helpfulness for scholars, industry professionals, and enthusiasts in seeking to understand the profound implications of AI on the modern music industry.

4.1 Thematic Reviews

This section will summarize and introduce the main findings of the most relevant literature. The twofold structure already mentioned will be used. First, literature about AI use in digital distribution will be presented through genre identification, music recommendation, or playlist curation, and second, the most relevant literature on AI and digital music production will be outlined. Each section starts with identifying what music distribution providers and AI tools are mentioned. Following this, a chronological assessment from the least to the most recent of the corresponding publication per theme follows in yearly increments. This helps reveal trends in the progression of the research field and shows how academic discourse develops.

4.1.1 Identifying AI Use in Digital Music Distribution

Clearly defined AI tools for digital music distribution are not named in the literature because these, as such, do not exist or are not disclosed since they are reserved for company stakeholders in the form of internally programmed computer systems. Nonetheless, what we can do is follow the task-based definition outlined earlier to examine streaming services and their techniques to find a framework for the categorization of streaming app features that demonstrate the application of intelligent computer systems by streaming stakeholders, thus allowing us to identify general AI usage. The task within the context of music distribution and company profit maximization is enhancing the listening experience of consumers and the exposure of artists. Consequently, any machine system in streaming that can be deemed intelligent in the broader sense due to neural network model and deep learning integration can be considered evidence of AI use.

Born et al. classify algorithmic music recommendation in today's music streaming landscape as a sociotechnical phenomenon embedded within the context of cultural music consumption. They acknowledge that recommendation systems are collectively designed tools with data scientists, algorithm programmers, product managers, and many more people taking part in the design process. Born et al. argue that, like any technology, music recommendation systems are shaped by stakeholders with assumptions about the nature of users, the problems being solved by this AI technology, and music itself. This implementation of AI impacts not only music culture as a whole but the neoliberal subject, the music listener, on an individual cultural level (Born et al., 2021).

How can we categorize music recommendation processes, and most importantly, how can we tell from an interface of a music streaming platform, in practice, that AI is utilized? Jannach et al. (2018) and Hesmondhalgh (2023) suggest possible ways of categorization that help us build a guideline.

Firstly, Hesmondhalgh puts forth that recommendation systems take different forms across streaming platforms because no streaming app is identically structured as another. However, this means that the common denominator seems to be that all modern music streaming services use some form of algorithmically-driven recommendation system based on CF, CBF, and hybrid or contextual approaches that can be identified in its interface and thus be considered proof of (possible) AI integration. Secondly, Jannach et al. classify apparent recommendation tasks in streaming apps as non-personalized and personalized and non-contextualized and contextualized (Jannach et al., 2018). Recommendation features may either belong to one or both of the categories. Combining these two insights, we can now form a general guideline that can be applied when looking at streaming apps in order to list algorithmically-based music recommendation techniques. All the most popular streaming apps such as Spotify, SoundCloud, Deezer, Pandora, YouTube Music, Apple Music, Tidal (Hesmondhalgh, 2023), and many others can be assessed according to the guideline.

The guideline groups recommendation user features in an app's interface as (i) feeds and trending, (ii) personalized recommendation based on likes and listening history, and lastly, (iii) curated playlists based on (non-personalized) context such as activities, moods, or specific genres. Whether all, some, or none of these types of techniques *are* AI is a philosophical discussion regarding nomenclature and definition scope. Most current literature suggests is that there are good grounds to claim that algorithmically-based music recommendation systems have evolved in a manner that makes them AI. Table 1 demonstrates the established guideline with the example of music recommendation features on SoundCloud (Soundcloud, 2024). Mind that there are possible overlaps in Feed features and curated playlists because these may include both context and content-based filtering approaches in the curation process, making the categories non-rigid. In other streaming apps with a similar structure,

Feeds & trending	Curated playlists based on listening behavior	Curated playlists based on context
• **"Feed - Discover":** A scrollable front page feature to find trending releases based on who you follow. The features "Feed - Following" and "Latest from artists you follow" are strictly showing new releases by who the user follows, and thus do not necessarily qualify as AI features because these are not based on hybrid filtering and AI-powered deep learning algorithms.	• **"Track Station":** A feature enabling the user to start his own radio station that uses the song with which the radio playlist is started as inspiration for songs that play next. • **"Made for You: Daily Drops":** A curated playlist based on app use behavior that is updated daily. • **"Made for You: Weekly Wave":** A curated playlist based on app use behavior that is updated weekly. • **"Yearly Playback":** A playlist curated automatically in yearly increments consisting of most listened tracks of the year. • **"More of What You Like":** A compilation of multiple curated playlists taking one song you listened to as an example. • **"Mixed for You":** A compilation of multiple curated playlists taking various users you follow as an example. • **"Curated to your taste":** A compilation of playlists such as " Tracks of the Week", "Ascending: Rising UK/IE Artists", or "First Listen". These playlists combine listening behavior and trending uploads to recommend songs to the user.	• **"Artists to watch out for":** A compilation of multiple curated playlists based on what the app's algorithms consider trending. This feature curates based on context because it takes a particular genre or subgenre as an example for its recommendation to the user. • **"Trending by genre":** A compilation of multiple curated playlists based on what the app's algorithms consider trending on SoundCloud with a context filtering approach of not only genre but also geographical region of the user. • **"Vibes":** A compilation of multiple curated playlists containing music that fits a certain activity or mood.

Table 1: Guideline for algorithmically-based recommendation features in a streaming app user interface applied to the example of SoundCloud.

these features may be named differently or serve different user preferences but nonetheless fall under these three categories.

4.1.2 Chronological Review of AI in Digital Music Distribution

To start the chronological review, J. Mason et al. identified how modern music consumption had formed over 30 years up to the article's publication in 2010. Benefits and doubts on three music access forms are discussed: downloading, streaming, and digital lending. The research aims to enable a better comprehension for music librarians and curators in helping consumers locate and utilize new digital options for music discovery. The paper provides a sophisticated overview of the necessity of monitoring and documenting the landscape of music access due to its rapid developments. At the time of publication, a critical issue seems to be a lack of standardization and research of different models of music provider services. Therefore, the paper correctly identifies research gaps and a pressing need for further research within the sector due to a paradigm-changing push in music access technologies.

Two years later, in 2012, Y. Song et al. succeeded in attempting to address the research gaps mentioned above and explore state-of-the-art technology in music recommendation in more detail. In "A Survey of Music Recommendation Systems and Future Perspectives", Y. Song et al. (2012) acknowledge the rapid expansion of digital music formats and the significance of further research on the one hand, and the fact that music recommender systems are still in their early stages in development on the other. This is despite the fact that music information retrieval (MIR) techniques were in current development at the time of the research. Song et al. recognize the importance of the field of research because of the juxtaposition of frequent usage of other leisure activities or media forms, such as TV or reading books, with that of listening to music. They argue that research on listening to music and, correspondingly, finding new music is lacking compared to other activities. After postulating that listening to music is a highly subjective, universal, and emotional activity, Song et al. propose a motivation-based model for future user-centric research. The paper surveys what they call a "general music recommender framework from user profiling, item modeling, and item-user profile matching to a series of state-of-the-art approaches" (Song et al., 2012, p.396). According to the authors, CF and CBF models perform well enough but show limitations regarding long-tail songs. Research gaps and problems identified include but are not limited to a lack of integration of musicology and music psychology in the technological investigation of subjective music recommendation systems, the high price of obtaining user data, or cold-start issues and popularity bias in hybrid filtering. Subsequently, the paper proposes to conduct empirical studies in human behavior to improve dynamic evolvement, user interface design, and playlist curation.

Leading Stanford computer scientists J. Pham, E. Kyauk, and E. Park (2015) achieve even further elaboration by moving away from music recommendation techniques for streaming and delving into further analysis of applications in hit song science. Various machine learning algorithms programmed with the Million Song Dataset (MSD), such as the support vector machine (SVM) supervised learning algorithm, are analyzed to identify the most fruitful techniques in hit song prediction. The MSD is a large-scale collection of song metadata such as artists' names, song titles, genre, or duration, and acoustic features such as beats per minute (BPM), musical key or loudness, and sound texture. It was created as a joint project of The Echo Nest and LabROSA at Columbia University (Bertin-Mahieux et al., 2011). The dataset has proven to be of particular importance for MIR researchers and computer scientists, e.g., to train algorithms for machine learning (Jannach, 2018). Pham et al. find that metadata is more predictive than acoustic features when applying a Gaussian Discriminant Analysis (GDA) kernel in SVM classification tasks. GDA is a type of statistical method in music genre classification (Phan, 2019). Pham et al. ultimately suggest that further research should focus on song popularity based on song recommendation and metrics based on the number of plays and downloads as a marker of popularity. In simpler terms, machine learning algorithms used to recommend and predict should be trained with datasets of the most popular songs to identify what metadata and acoustic features statistically lead to the highest degree of popularity.

In the same year, Schedl et al. (2015) conducted a famous comprehensive study of the state of the art of music recommender systems, capturing different types of filtering, datasets, or evaluation strategies and challenges. One main finding is that music recommender systems face unique challenges compared to other media domains, such as video and film, due to the shorter consumption times, repeatability, and high quantity of consumed content. A second finding is that context-aware recommendation techniques were still in prototype stages while simultaneously becoming more prevalent. Context-aware music recommendation positions pieces of music in a more holistic scope because mood, activity, or weather are decisive factors. According to Schedl et al., hybrid recommender systems should be trained with multiple different types of data sources. Furthermore, the kinds of data influencing human user perception of music should be better understood.

In 2018, Millecamp et al. conducted a within-subject Latin Square design study to evaluate the impact of having Spotify consumers use radar charts versus sliders when discovering new music by adjusting the levels of different metadata or acoustic features of songs they already liked. They found that more long-term and musically knowledgeable consumers used the radar chart more than sliders, which confirms the usefulness of possible implementation of the feature to give users more control and implement visual cues into the process of controlling personal recommendations instead of not being able to interact with the recommendation process at all and only seeing its outputs in the app. While such features are reserved for employees, they have not been implemented for users in the app as of today. The study emphasizes that there is somewhat of a "black box problem" regarding the transparency in the process of getting music recommendations by an app's algorithm; the user does not know how the application programming interface (API) is used by programmers to have the AI algorithm generate suggestions (Millecamp et al., 2018). What makes this study especially compelling is the idea of implementing more user interaction and possibilities to control one's own song recommendations.

The fact that Spotify had been adopting high levels of AI usage and has made remarkable investments that affected its brand-consumer relationship in multiple ways was empirically studied by van de Haar et al. one year later, in 2019, using a qualitative case study approach. Ultimately, the authors found that AI-driven personalized services significantly enhance this relationship and that this trend can be expected to grow further. Likewise, AI influences the way in which music is consumed and discovered positively. This trend is also expected to grow stronger in the future. While these findings can be proven correct, there may be potential biases due to the amount of secondary data sources in the study and, with that, a lack of primary research and interviews of technology and business psychology experts in the field make precise predictions about the future of AI more challenging (van de Haar et al., 2019). The paper acknowledges that there was limited peer-reviewed research at the time of publication, which, combined with having used a single case study approach, can potentially impede generalizability.

Moving forward, U. Dolata (2020) performed a thorough historiographical and socio-economic analysis of the repercussions of the technological transformations within the music industry since the 90s, focussing on the institutional structure. While the paper does not focus on digital music distribution, it provides crucial insight into the entire sector and, therewith, also into the socio-economic context in which the streaming sector is situated. Dolata argues that the pressure to change became so imminent that after great hesitance, music companies were finally forced to accept the change. Dolata identifies five factors that contributed to the hesitance in adapting to the sector's new and fast-paced technological challenges. First, difficulties in anticipating novel technological opportunities; second, tortuous processes of techno-institutional natch establishment; third, technological conservatism; fourth, an overly oligopolistic sector; and lastly, focal companies being too hierarchically structured (Dolata, 2020). Congruently, Dolata has established four stages of technological advancement within the music industry. These stages are the digitalization of audio media, followed by the rise of free music file-sharing and the subsequent commercial sale with widespread distribution of downloads when eventually reaching the final culmination of commercial streaming. It is also mentioned that the technological change was brought about in unison with external actors not affiliated with the music industry, resulting in the groundbreaking development of how music is accessed and shared today. Dolata concludes that while the changes appear to be radical and technology-driven, the sector will likely see a gradual transformation over a longer period of time.

One of the most essential factors of technological change is the development of genre identification techniques. Elbir et al. (2020) deem genre classification to be one of the most crucial parts of meeting consumer needs to find the music they prefer listening to. The authors argue that MusicRecNet, a genre classification tool with implemented CNNs, performs better than its competitors because it achieves high accuracy and also uses plagiarism detection. MusicRecNet was found to work the best with classical music, while rock music classification was the most challenging to the deep neural network system. Looking back, there is no evidence that MusicRecNet is being used for the genre classification activities of major streaming providers such as Spotify, which acquired The Echo Nest in 2014 and has now integrated its services as a house-owned Spotify-API not publicly available anymore (Yu, 2024). Adding to this possible limitation of the findings in Elbir et al. (2020), Chamola et al. (2021) argued that LSTM models are significantly more stable and accurate than CNN or RNN models when classifying audio signals. However, further training in more novel LSTM-based models is needed.

A leading British professor of media, David Hesmondhalgh, has published a range of papers on streaming and the sociocultural complexities within the digital media economy (ResearchGate, 2024). In September 2021, he published the article "Is Streaming Bad For Musicians? Problems of Evidence and Argument". The paper discusses controversies surrounding music streaming services and their impact on artist earnings through a comparative analysis with older media outlets such as radio or physical sales. It also explores criticisms and possible improvements, such as user-centric payment models. It finds that while more artists may get sufficiently paid, significant inequalities and poor working conditions persist, which should be tackled by providing better transparency (Hesmondhalgh, 2021). The research leaves the possibility to be elaborated on by performing longitudinal research on earnings and imbalances within the sector. The second chapter of this literature review will provide an overview of the literature that ties into the research performed on the role of innovative technologies from the artist's standpoint.

A striking white paper by Born et al. was published in 2021, which situates and critiques music recommendation technology in the context of the neoliberal economy of creativity vs. the intellectual property of diverse creative communities or smaller artists and music as a creative endeavor. The paper finds AI use in the form of music recommendation to have significant transformative impacts on cultural experiences and industry dynamics. AI music recommendation tools are sociotechnical systems shaped by the assumptions on music consumption and distribution of their designers. Taking a philosophical and sociological approach, Born et al. argue that the recommendations generated have the potential to reinforce global commercial popular music at the expense of diverse local or traditional styles, perpetuating biases embedded in the design processes and thus triggering reinforcement loops because once priming and favoring a certain way of recommending, the systems learn from their own outputs over and over again. There is enough reason to believe that there is limited demographic representation among developers and decision-makers, which can threaten inclusivity and boost cultural bias and overcommodification in the form of short, marketable music. The influence of AI extends beyond consumption to the creation of music. According to the authors, artists may end up increasingly tailoring their work to fit platform algorithms, which might threaten creative freedom in the long run. AI also automates parts of the industry, such as Artist and Repertoire (A&R) functions, exemplified by SNAFU Records' use of AI to identify emerging artists or Sodatone. Human expert skills, such as editing or facilitating, might become secondary roles, while the systems themselves lack transparency in how they assign value to music and creators.

Furthermore, the paper suggests that AI-driven recommendation systems favor personalization at the possible expense of shared cultural experiences or minority musical culture, which leads to cultural homogeneity on the long run. Algorithmically primed bubbles limit exposure to diverse musical content and discourage exploring musical diversity. When cultural horizons are narrowed, implications for societal connectivity and shared cultural knowledge are threatened.

Gaps in current approaches to AI in the music industry are also identified by the authors. Existing AI computer systems largely neglect cultural diversity, failing to adequately represent non-Western, traditional, or experimental music styles. This is constantly recurring theme in the literature reviewed. Transparency and accountability issues highlight ethical concerns about data privacy, user empowerment, and labor market fairness. An emphasis on profit-focussed metrics overshadows the need to prioritize cultural and social values in ethical platform design.

To address these issues, the article suggests future perspectives in which the integration of AI in the music industry shall be reevaluated. Future research should further implement diverse cultural and social contexts to guide AI system designs, enabling algorithms to better reflect and secure the plurality of global and cultural musical traditions (Born et al., 2021). The paper addresses ethical gaps and uses a multidisciplinary approach, that calls for envisioning a future where AI enhances, rather than limits, the richness of music culture.

In the course of 2021, a lot of valuable scientific research focussed more on AI and music generation and more in-depth analysis of recommender systems in computer science. However, there is one specific paper with great academic relevancy. Anantrasirichai & Bull (2021) wrote a comprehensive and well-executed literature review on AI in the entirety of the creative industries. It explains basic AI terminology and categorizes the use of AI across various sectors, such as music, art, or entertainment media. The authors conclude that machine learning AI will be widely adopted and take the role of a collaborative assistant in creation processes while AI's ability to become an independent creator remains modest, this is, in 2021. As the remainder of this paper will show, however, quick advances in generative AI might contradict this finding or at least provide material for counterarguments. Another core finding is that the authors state that the maximum advantage of AI implementation in the creative industries comes from the augmentation of human creativity rather than a replacement of it. Taking the approach of improving generative AI in creativity instead of trying to fight it and brush it off as an enemy of human creativity is especially interesting when compared to other literature or artist opinions.

Let us now examine a research conducted by Hesmondhalgh published in 2022. Hesmondhalgh's "Streaming's Effect on Music Culture: Old Anxieties and New Simplification" from 2022 examines five points of critique of music streaming platforms and rates their validity. Correspondingly, these points are related to older anxieties around the industrialization of music to suggest a more nuanced critique. In this context, the author finds that many recent critiques of streaming are rooted in old anxieties about technological impact on music. This may lead to elitism or over-simplification. Criticisms of a positive outlook on streaming and the arguments of blandness and passivity being attributed to modern digital distribution often rely on outdated notions of musical autonomy and overlook the complexity of musical practice. Research gaps that can be deducted from the research can be broken down into two main points. First, there is only a scarce amount of research concerning the impact of streaming on the musical experience as a cultural phenomenon, and second, there is a lack of critical accounts situating streaming platforms within this cultural realm in a more sophisticated manner.

From 2022 to 2024, the amount of literature on AI in music has significantly increased in both streaming or creativity and cultural scopes of research. Baracskay et al. adopted a more cultural scope in "The Diversity of Music Recommender Systems" (2022). While the study lacks greater popularity, most likely due to the fact that it is a rather niche and narrow topic, this speaks for the uniqueness of the research. The authors argue that on the one hand, algorithms in music recommendation processes have been researched quite while on the other, there is little to no research on "studying the nature of their recommendations within the full context of the system itself" (Baracskay et al., 2022, p.97). This Clemson University research zooms in on five popular streaming services, namely, Spotify, YouTube Music, Apple Music, Pandora, and Last.fm. Somewhat surprisingly, the authors find that Spotify recommendations, when compared to the other four services, were the least diverse when provided with the artificially curated input playlist. YouTube Music scored highest on the diversity level. Regarding possible future work, the paper suggests that other authors could delve deeper into how different recommendation techniques may result in different levels of diversity. A potential limitation of this study is that Baracskay et al. only tested one playlist for each of the diversity levels; future work could use multiple playlists for each level of diversity or use playlists made by real users rather than artificial ones. Upcoming research could delve deeper into existing reviews and/or supplement these results with user surveys. Lastly, studying the option to let users disable the recommendation feature could yield fruitful academic results.

In 2023, Hesmondhalgh et al. published yet another study on music recommender systems. This time, we are looking at a comprehensive literature review. The research distinguishes between technical and critical perspectives on music recommender systems, highlighting that academic computer science endeavors often focus on enhancing technical efficiency. In contrast, critical research addresses societal and cultural implications. Computer science research most often examines relevance, bias, and user satisfaction but lacks depth in the contextualization of recommender techniques in the social sphere. There are significant concerns within music recommendation in the form of popularity and demographic biases, which favor widely known artists and pose potential challenges to musical diversity or artist representation. Notable research gaps that the literature finds in preexisting research include a lack of collaboration between technical and sociocultural fields as well as limited access to real-world data from music streaming platforms because valuable data is often not available to the public due to business non-disclosure regulations. This leads to a further lack of research on the impacts on user experience, especially on the qualitative side. Further scientific investigation is needed to understand the demographic biases within these systems, such as potential disadvantages based on gender, race, and nationality. The authors suggest that interdisciplinary research is needed to fully understand the societal impact of music recommendation, encouraging studies that consider ethical implications, demographic biases, or popularity dynamics. Interdisciplinary studies should address the issues of fairness, transparency, and diversity. Analyzing public policy implications, such as transparency and oversight within the streaming business, can potentially improve a progression toward a more inclusive music industry.

A reasonable amount of interdisciplinary research attempts are made by Biazzo & Farné (2023). Even though their paper is part of the International Journal of Music Science, Technology & Art, with a statistically driven computer science approach, they implement the factor of mood-based personalization in Spotify playlist curation. In the paper, the authors review types of recommendations and discuss technical challenges, primarily in Spotify playlist curation. Subsequently, they stress the need for hybrid techniques and the quality perception of the user. All mood-based clusters, energetic, good vibes, cheerful, and chill, were identified, and all show significant prediction performance in creating playlists depending on the listener's mood. The interdisciplinarity of the research is not achieved by combining different fields of academic study, such as computer science and musicology, but rather by implementing the qualitative music psychology factor of mood. This acknowledges that mood is a critical phenomenological context within which music listening is embedded.

Moving forward, in 2024, one study can be linked back to the notion of a lack of transparency regarding music recommendation techniques, as previously mentioned, to be identified by Millecamp (2018) and Hesmondhalgh (2020 & 2023). To round up this subsection, Murindanyi et al. (2024) outline a responsible AI-based music recommendation system based on classic machine learning and deep neural networks for accurate genre classification while ensuring better transparency, accountability, and minimizing risks. This research succeeds in filling the research gap of addressing ethical and social implications regarding music recommendation, an approach that has been lacking academic analysis over the last decade. The authors call their model responsible because they apply explainable AI techniques such as

Shepley Additive Explanations (SHAP) and ELI5 to provide interpretable explanations for the decisions made by the recommender system. Adding to the "black box" problem we have seen mentioned in Millecamp (2018), Murindanyi et al. argue that music recommender systems themselves can influence music preferences and user choices, leading to possible privacy concerns or so-called filter bubbles, meaning the use of algorithms primes the user output to a degree with which there ultimately is a limitation to exposure of diversity. The study finds that the deep neural network model implemented in the study had a 93% accuracy rate on training and test data sets. Model interpretability can be further ensured by the applied SHAP analysis. SHAP is an explainable AI technique that aids in the oversight of why certain features were retrieved in the decision-making process (Murindanyi, 2018). From a critical standpoint, a potential limitation of the study does not regard its excellent findings but its practical reality. Proving that responsible AI techniques are both reliable and highly efficient ensures a big step towards ethical AI use in the music sector. However, whether large stakeholders such as Spotify or Apple Music adopt these processes and act in due diligence remains a matter of business decision-making discretion. Furthermore, the consumer of streamed music may still never know how a music recommendation was made; ergo, the "black box problem" still remains mostly unsolved.

4.1.3 Identifying AI Use in Digital Music Creation

Contrary to what we have seen with AI use in digital music distribution, naming specific AI tools used in digital music creation is a more clear-cut and straightforward task. AI tools in music creation are often products in the form of VST plugins for DAWs or computer software that is publicly purchasable for both amateur artists and professionals as well as companies. This makes categorizing them easier on the one hand, on the other, however, the demarcations of categories are often blurrier compared to music recommendation systems, and even though the AI tools are easily identifiable, there is no finite number of tools, let alone application possibilities of said tools. With the pace of current development and the state of the industry, we are looking at a rapidly rising number of AI tools that assist or replace human music creation (processes).

The most recent and comprehensive study performed on the topic was conducted this year by Goldmedia (2024) and funded by GEMA. The over 170-page long, multidimensional study encompasses all major aspects of AI in the music industry by discussing historical milestones, investments, industry facts, and categorizing or naming companies, brands, and tools used in the current state of the industry. We will now review the study to ultimately extract what AI tools and categories thereof are used in music creation.

After the CD, downloading, and streaming era from 1997-2009, 2010 marked the first year in which AI tools were being used in music, with the first computer-generated songs being created. Sony started developing Flow Machines in 2012, seeking to automate music composition. Google joined the market niche in 2016 with their production assistance tool, Magenta. In 2017, the controversial matter of deep-fake production in video and audio production started, and by 2018, the automated music generator Boomy was released. Even before the bulwark event of OpenAI's ChatGPT being released in 2022, the company released MuseNet, which is a deep learning neural network model that can also be integrated into music generation. ChatGPT's release and its consecutive popularity triggered a large amount of AI tool developments either directly or indirectly by shifting the attention of stakeholders, artists, and consumers to new possibilities and technological innovations in music composition (Ibid.).

Goldmedia conducted an analysis of the music AI ecosystem based on data gathered by Edwards & McGlynn (2023), from which AI companies or their tools taking part in the music sector transformation can be listed according to nine categories: composition/songwriting, texting, sound and sample search, voice and speech synthesis, audio synthesis, audio transcription, editing of audio sources, mixing/mastering, and others.

Starting with composition and songwriting, the most notable AI companies in the category include MusicLM, Jukebox, Meta's MusicGen AI, Boomy, Loudly, Soundraw, Musico, and many more. Sudowrite or These Lyrics Do Not Exist are texting AI tools, while Musiio, which was acquired by SoundCloud, is an example of a sound and sample search tool. Others include Waves, AudioStellar, or Splice, the frontrunner sample search tool for current professional music composition. Voice and speech synthesis tools are Wellsaid, Descript, Supertone and others. Mubert, Harmonai, or Never Before Heard Sounds, amongst others, are used for audio synthesis. Klangio, BasicPitch, and AnthemScore are popular audio transcription applications. The editing of audio sources is aided by AI tools such as Audioshake, Spleeter, which is a tool with which streaming platform Deezer joined the music composition market, or Demucs. The process of editing loudness or EQ levels of synths in a song at the end of a studio production process to make a raw production sound less mushy and make it studio-quality-sounding is called mastering. The main objective here is to balance and equalize all different sounds in the song so that none overpowers another in loudness or frequency. This significant part of professional music production is assisted by applications such as iZotope's Ozone 10, BandLab, or Landr, to name only a few crucial software. Lastly, software like LALAL.AI falls under the "other" category. This app uses AI models to extract so-called stems from musical pieces. Meaning that from a song, one can separately extract only its drums, its acapella, the full instrumental, or other audio tracks within a song. This process is integral to remixing or producing mashups of two different songs (Ibid.).

Google, Meta, OpenAI, Shutterstock, and stability.ai provide the majority of foundation models used by other companies for the development of their software's language or deep learning neural network models. Some of these include PaLM 2 (Google), LLaMA (Meta), GPT-4 (OpenAI), MPT-7B (Shutterstock), and Stable Diffusion XL (stability.ai). PaLM 2 is used by MusicLM, LLaMA by Meta's MusicGen AI, GPT-4 LLMs by MuseNet and JukeBox, MPT-7B by Amper, and Stable Diffusion XL by Harmonai and Stable Audio.

Goldmedia's study suggests a categorization scheme of AI tools in music composition that labels them as either descriptive or generative AI tools and sorts them by three categories based on their field of application in the music production process, which hold sub-categories that are either descriptive or generative in nature. These are (i) creative aspects such as composition, texting, or arrangements, (ii) recording, editing, mixing, and mastering, and lastly, (iii) supporting aspects (Ibid.).

Descriptive AI in the music-making process refers to a type of AI that is applied in analytical and enhancement tasks such as genre identification or musicological research and marketing or hit detection, aiding users in understanding patterns in music or refining their own musical composition in music production. This type of AI analyzes and interprets existing music data. Contrary to generative AI, descriptive AI does not create new content but provides insights for enhancements of a composition to speed up, simplify, or diversify the music production process.

Generative AI tools in the music-making process are plugins or synthesizer software that compose new and original music content by learning patterns from large datasets of preexisting music. They use algorithms and deep learning techniques based on the datasets of compositions that were used to train them to generate parts of songs such as melodies or MIDI patterns or even entire songs from scratch. AI tools that, i.e., generate deep-fakes or imitate voices and synthesizers and often get notable amounts of recognition in public discourse for this, are generative AI tools (Chow, 2023). It is important to note that these two distinctions are not mutually exclusive. AI tools may have properties of both types but generally share more with one type than the other.

Creative aspects such as composition, texting, and arrangement are made up of eight core sub-categories that are either descriptive or generative in nature. These are sound search, sample search, audio-to-music notation sheet translation, creation of lyrics, dynamic editing, instrumental synthesis, sectioning, and complete composition. Cyanbte and Musiio are generative sound search tools. Splice and Musico are examples of generative sample search tools. AnthemScore and Klangio are descriptive audio-to-sheet notation tools. These Lyrics Do Not Exist and Sudowrite are generative lyrics creation AI tools. Generative dynamic editing tools include Orb or Evoke Music. MuseNet and Mubert are AI tools used for instrumental synthesis processes, while AIVA aids in sectioning processes. MusicGen AI, MusicLM, or Boomy are popular generative AI tools that provide complete composition services.

Recording, editing, mixing, and mastering processes can be broken down into four sub-categories, namely, voice and speech synthesis or cloning, editing and manipulation of sound, correction and cleaning of sound, and lastly, mixing and mastering. Examples of generative voice and speech synthesis AI tools are VOCALiD, Supertone or Wellsaid. Editing and manipulation of sound can be performed with descriptive tools such as LALAL.AI or Basic Pitch, while audioshake and Audo Studio can more so be considered sound correction and cleaning tools. IZotope, Landr, AI Mastering, and Cryo Mix are descriptive AI-powered tools prevalently used in sophisticated mixing and mastering processes.

Supporting aspects in the music composition process are split into three descriptive AI sub-categories and can be understood to indirectly impact music production. Music promotion and trend prediction are performed with the help of Hitlab, Musiio, or Sodatone. The strongly related subcategory of peer group distribution or user data analysis can be conducted with the help of tools such as Symphony AI or Fanify (Goldmedia, 2024).

4.1.4 Chronological Review of AI in the Context of the Artist and Industry

After examining the course of literature published on music recommendation processes and their context, and zooming in on the Goldmedia study to name AI tools in the composition process, this section provides an overview of scholarly literature concerning AI in digital music creation processes, the dynamics, and research performed on the state of the industry in relation to AI as a whole.

One of the first researches on AI-assisted music creation was done by Avdeeff (2019). The work discusses the first AI-human collaborated album, "Hello World," by SKYGGE, and correspondingly assesses AI in popular music production. The authors introduce the notion of an *audio* uncanny valley. The AI uncanny valley refers to the phenomenon where humanoid robots or objects resemble humans, but imperfections in their visual properties can evoke feelings of uneasiness or revulsion in the observer. The concept was first introduced by Masahiro Morias as early as 1970 (Seyama et al., 2017). In this context, the author finds that the idea of an *audio* uncanny valley describes the unease and excitement provoked by AI-generated music, which challenges classical notions of musical creativity. Avdeeff discusses the post-humanism, sincerity, and authenticity implications that come with AI use in digital music production. At the point of publication in 2019, the paper suggests that capabilities in AI-aided music production are quite limited in scope. The tools at that time were mainly collaborative assistance tools that helped produce novel sounds and melodies. The paper stresses a lack of research in popular music AI precisely due to this novelty of innovation. As we will discover later, however, in the course of 5 years, this changed drastically. A significant impetus for further research is established by pointing out that AI's effects on the human-machine relationship and human roles in this collaborative creative activity ought to be studied.

A year later, in 2020, Artemi-Maria Gioti explored said relationship, proposing a model of distributed human-machine co-creativity that could possibly enhance creative possibilities and better understand musical creativity. Gioti is one of the first scholars to suggest that computational creativity extends human creativity (Gioti, 2020). However, they acknowledge that, as we have already seen in the literature on music recommendation, computer systems often fail to integrate sociocultural and psychological factors. The theoretical frameworks used include extended intelligence (EI) and actor-network theory in creative ecosystems.

Multiple research gaps that can be deducted can be summed up as the importance of the capability of autonomous computers to create new acoustic styles and transform creativity in doing so. The influence on the artistic community plays an important role. Therefore, there is a call for further research to explore whether a positive transformation can be achieved and, ultimately, if technological innovation is capable of complementing human creativity.

E. Miranda edited a large compilation of academic papers on the topic of AI in music, publishing the *Handbook of Artificial Intelligence for Music: Foundations, Advanced Approaches, and Developments for Creativity* in 2021 on Springer. A particularly fitting paper in the book was written by P. Dahlstedt (2021). The essay critically examines the capabilities and limitations of AI and ML in creativity and music. The main argument proposes that while they are powerful tools, they lack true creative agency and primarily serve to distribute human agency rather than extend it. AI tools cannot be deemed autonomous creators. New creative horizons should be explored rather than focussing on the current ones. The biggest contribution to the field of research is made by raising ethical questions. These can be broken down to: What if AI tools are applied to fully imitate the creation of musical pieces that have not been heard before, and what does this do to agency and ownership rights? In sum, the most pressing issue seems to be that there should be further investigation of the consequences of having AI produce something without human interaction.

A second paper in the Handbook was written by Knotts & Collins (2021). It does not only explore the historical context and current state of AI in music production but also dives into the future potential of AI in music performances. This adds a novel perspective to existing scholarly discourse. Both experimental and commercial uses are discussed. After conducting an online survey of 117 participants, the authors found that the majority of respondents felt that AI has made production easier and influenced their style. However, few respondents rely on music creation as their main source of earnings. Still, most respondents do not believe that AI will cause widespread job loss or homogenization in music; in other words, they see AI as a threat to diverse publications of music pieces. Even though there seems to be somewhat of a common denominator, future research must continue to research the avoidance of cultural biases by reflecting on the diversity of datasets used as input for the training of ML systems. It is acknowledged that in 2021, broader implications of social issues remain mostly unaddressed.

Moving forward, yet another paper in the handbook, "Sociocultural and Design Perspectives on AI-Based Music Production: Why Do We Make Music and What Changes if AI Makes it for Us?" by O. Brown (2021) discusses the evolution of generative AI in music production with an emphasis on its philosophical origins and practical appliances by using wicked problem approach and sociological perspectives such as Durkheim theories. Brown finds that the recent AI boom caused a growing interest in trying out AI tools. At the time of publication, AI tools were deemed effective tools but often lacked human-like algorithms. The author takes a more positive approach towards AI implementation by outlining gaps in scientific discourse to, be the discovery of functional AI technologies that can generate music totally from scratch or the development of models that incorporate musical taste or the sophistication of human-like creative behavior. Overall, Brown (2021) seems to convey a positive outlook on advancing AI technology in music production.

After publishing their 2020 paper, M. Gioti followed up on their research on AI in music production with "Artificial Intelligence for Music Composition" (2021), which is also part of the Handbook of AI for Music. This time, the integration of AI in artistic practices is addressed by describing various AI tools. Gioti puts forth that machine learning algorithms offer possibilities in sound design, interactive music creation, and human-computer co-exploration of new musical opportunities. A major issue identified by the research is that there seems to be a high discrepancy between the close-endedness of machine learning tools and the open-ended nature of creative activity, exacerbating human-machine work. Interestingly enough, but not surprisingly, Gioti also mentioned the "black box" problem. In the context of AI-assisted music production, AI tools (at that time) had an automation architecture that did not leave room for enough interaction for the user to understand a certain acoustic output. The user can only feed the tool samples and have outputs generated that are not transparently understandable (Gioti, 2021).

From 2022 to 2024, musicological research about AI in music creation has seen an enormous surge. Moving on after Gioti's insights, Rohrmeier (2022) explores the intersection of human and computational creativity while addressing philosophical dilemmas and presupposing four challenges for AI musical creativity: cognitive modeling, external world references, embodiment, and meta-level creativity (Rohrmeier. 2022). Rohrmeier argues that addressing these challenges in the future can lead to improved developments in artificial musical creativity. Yet again, interdisciplinary exchange and cross-cultural research encompassing psychological, musicological, neuro-scientific, and computer-scientific approaches are called for. Creativity should be better modeled on a metadata level.

In 2022, the 3rd Conference on AI Music Creativity (AIMC 2022), an online conference hosted from Tokyo, Japan, has produced a range of papers of high scientific value. Ostermann (2022) e.g. proposes a new approach to algorithmic music composition by encoding musical taste as a binary classification task, which was demonstrated by a proof-of-concept experiment using neural networks. The research formalizes the concept of a composer-producer collaboration and enhances musical quality by treating musical taste as a binary and, therefore, quantifiable factor. Many other authors who participated in the conference contributed to computer scientific research in the matter. Due to the detailed and narrow scope of these findings, however, we will move on to listing a new and comprehensive book that have been published in 2024 with highly valuable insights.

Firstly, *Artificial Intelligence - Intelligent Art? Human-Machine Interaction and Creative Practice* (ed.) Voigts et al. (2024) is a highly interdisciplinary volume compiling papers on multiple academic endeavors ranging from musicology and sociology to computer science and technology. One example of an essay that can be found in the paper is "On Human-Machine Relationship and the Notion of an Artificial Intelligence in Music Practice" by S. Kunas. The essay emphasizes the complex relationship between musicians and technology and advocates for a shift in discourse toward an accomplishment of true human-machine hybridity in musical practice. The band Phuture, amongst others, is used to illustrate productive co-creation and critical engagement with the sociocultural embeddedness of musical practice. The essay postulates that the hype surrounding AI should be used as a driving force to understand the underlying hybridity that will sooner or later become clear within music creation. Kunas argues that the notion of democratization of music production through technology is a myth due to the ignorance towards underlying labor condition inequalities. A Research gap that ought to be filled in the future is that human-machine relationships should be further explored, and the discomfort behind it should be acknowledged and understood (Kunas, 2024).

Another convincing paper is "The Upcoming Change in Human Musical Thinking. What Does a Music Professional Do in the Age of AI?" by N. Braguinski (2024). Braguinski formulates an attempt to explore the future of musical knowledge about AI and examines which musical activities AI can imitate. It puts forth that these activities can change in the future. It answered the question regarding who would be interested in AI-based tools and categorizes existing innovative and future technologies while mentioning the adaptability of music theory and what impacts musicians might have to deal with moving on. Once again, a lack of interdisciplinarity is critiqued, and a need for roadmaps to prepare for future change is deemed necessary.

Lastly, a third example of an intellectually stimulating paper in the book is "Artificial Intelligence in Songwriting and Composing - Perspectives and Challenges in Creative Practices" by Tillmann & Zaddach (2024). The authors conducted qualitative interviews with music professionals such as songwriters and composers to analyze the impact of AI on songwriting and composition. They take a look at the benefits and challenges of doing so. The authors take a clear positive and, therefore, anti-skeptic outlook on AI in music composition and claim that AI adoption in creative musical practices can enrich artistic expression. They clearly state that AI will not replace the artist but, as older technological innovations did, act as an extension of the artist's creative inspiration and toolbox (Tillmann & Zaddach, 2024). Collaborative research in AI labs is suggested as a method for future artistic research. AI, the authors argue, should be integrated into music education curricula, too.

5 AI Applications in Distribution and Creation

5.1 Distribution: Spotify & Co.

The innovative digitalization of the music industry arguably started with the peak of CD sales, following the vinyl and record store era in 1997. By 1999, Napster, the pioneering forerunner of today's music streaming industry, was founded (Goldmedia, 2024). Because many users found themselves breaking copyright laws by burning CDs as a way of distributing and sharing their music, Shawn Fanning founded Napster with a user-friendly interface, changing the way music was digitally distributed forever because it let users dully download music and have them play their songs without an internet connection. Users could surpass breaking copyright laws and had a new comfortable way of listening to music (Mason & Wiercinksi, 2010). The distribution of music, therefore, went from hardware to digital downloading and lending to real-time streaming platformization.

By 2006, Spotify was launched, marking yet another milestone, starting the streaming era. The streaming service Spotify, founded in 2006 by Daniel Ek (Music Business Worldwide, n.d.), has established itself as the most household name in music streaming and set itself apart from its competitors with its highly personalized music recommendations in such a way that it can be considered the pinnacle of worldwide music streaming success (Schwarz & Johansson, 2022). With advanced AI algorithms, Spotify has become the number one discovery platform that curates playlists uniquely suited to its customers. Through features like "Discover Weekly" and "Daily Mix" (Volovik, 2024), Spotify offers features that enhance user engagement like no other streaming service and, therefore, sets itself apart with over 600 million (Singh, 2024) active monthly users (Yu, 2024). This case study mentions two examples of AI integration. Firstly, Spotify's AI is used in recommendation and playlist curation, and secondly, AI is used in hit-song detection by some of the most decorated music labels such as Warner, Atlantic, BigBeat, or popular house music genre Spinnin' Records, with Sodatone. Future perspectives of Web3.0 and blockchain technology in this context are outlined. Ethical and sociocultural implications are discussed to argue that while AI use is a driving force in the advancements of the digitalized music economy, it accumulated issues such as an over-commodification of music as art, which has various effects on stakeholders in music culture.

5.1.1 Industry Facts

Spotify continues to lead the music streaming market with a market share exceeding 33% as of 2023 (Spotify Annual Report, 2023). As reported by S. Singh on Demandsage, Spotify accumulated a staggering 246 million paid subscribers and another 280 million users on its free, ad-supported tier, with which it generated a revenue of over 845 million euros (Singh, 2024). Streaming revenue now constitutes the majority of the entire global music industry income. Streaming accounts for 67.3% of total industry revenue (IFPI, 2024). In the United States, the RIAA (2023) reported that paid subscriptions accounted for $11.2 billion in revenue. Over the course of 4 years, from 2021 to 2024, Spotify was able to almost double its number of premium subscribers from 158 million to the mentioned amount of 280 million (Singh, 2024). These numbers strongly suggest that Spotify succeeded in converting users from free to premium active users with the help of its technological advancements. The time span lines up with the rise of research in the era and the AI boom. Spotify, therefore, played a leading role as a piloting stakeholder in the transformative change in the industry from physical sales to globalized on-demand streaming through subscriptions (RIAA, 2023). Since 2013, Spotify has gone on a spree of acquisitions, AI integrations, and feature developments. In 2013 Spotify acquired Tunigo to assist their music recommendation systems. During this time, research was very scarce and music recommendation was in its infancy, which yet again proves that Spotify secured a competitive advantage before other streaming services (Mason & Wiercinski, 2010). Only a year later, in 2014, the acquisition of The Echo Nest took place (van de Haar, 2019), which, as we have mentioned earlier in this paper, later became an integral part of Spotify's house-owned MIR API. From 2015-2017, the music recommendation, audio detection, and search services Seed Scientific, Sonalytic, and Niland were acquired (Volovik, 2024).

Next to the application field of streaming, AI use spans to other areas, e.g., to the artist and repertoire (A&R) departments of major labels in the industry. Sodatone is a fully automated and AI-powered computer system that provides industry experts with scouting tools and, therefore, acts somewhat like a non-human A&R agent, or at least as a machine collaborator in the process of talent discovery (Sodatone, 2024). It was founded in 2016 and thereafter acquired by Warner Music Group in 2018 (Rocchi, 2020). Sodatone applies predictive analytics to identify promising artists and potential hit songs based on streaming metadata, social media dan engagement, and genre classification deep learning techniques (Pham et al., 2015). This AI-powered tool aligns with the broader trend in the music industry, where data-driven insights shape artist discovery and marketing strategies (Rocchi, 2020). According to its website, Sodatone claims that it holds the industry's most comprehensive dataset, containing over 8 million artists, 250 million digital service provider (DSP) releases, and an astounding amount of 2.7 billion short-form videos (Sodatone, 2024). Sodatone challenges traditional music scouting by venturing into the field of big data, acknowledging the possibility that not only music discovery by consumers but also by experts and labels will most likely be at least partially automated in the future.

5.1.2 The APIs of Spotify and Sodatone

Spotify's recommendation techniques encompass multiple AI models, such as CF, NLP, and deep learning, making its recommender system hybridized. The foundation of this system is constituted by the Bandits for Recommendations as Treatments (BaRT) algorithm (Aoun et al., 2022), which enables the balancing of content that is already available for consumption with constantly emerging novel suggestions. (Spotify Annual Report, 2023). However, as we have seen in the literature review section of this paper, most of Spotify's AI techniques are not disclosed to the public, other than the fact that The Echo Nest is behind its system applications, as Spotify's Research department leaves the reader with little detailed insight (R&D Research, 2024).

Hybrid filtering is inherent to Spotify's recommendation models. Through the combined use of collaborative filtering and content-based filtering, Spotify can merge the advantages of two different techniques. First, CF can identify patterns across users, and second, acoustic feature detection in CBF and genre classification rounds up the model by providing better-suited output to the customer. Existing music data analysis and close observation of real-time listening behavior are performed (Song et al., 2012). Spotify is, therefore, able to create personalized listening experiences that feel intuitive and unique (Anand et al., 2021). Adding to this, Spotify employs NLP in order to analyze text such as song lyrics or artists' bios. This analysis ensures the recommendation of music not only by genre but also by theme or even emotional atmosphere, which ultimately aligns customer interest with what the AI systems put out as suggestions. The categorization of songs beyond genre is, therefore, not only a useful gimmick but a crucial economic advantage when compared to other services such as YouTube Music, SoundCloud, and co. (Castillo et al., 2023). Deep neural network models such as CNNs or LSTMs further deepen the precision and efficacy of the AI systems at play. Spotify's approach honors explicit preferences of users and implicit factors regarding tonal inclinations lead to a well-rounded reflection of the user's musical interests. In practice, a user that listens to a specific subgenre of music, such as Tech House with a beachy feel, would get songs suggested to them that fit exactly this type of subgenre and tone (Ibid.; Biazzo & Farné, 2023).

The "Discover Weekly" function was introduced in July 2015 (Luebbers, 2020) and is the flagship music recommender output of Spotify's AI-driven music discovery (Aoun et al., 2022). Every Monday, users are provided with a curated playlist tailored to their preferences and tastes based on recent listening history and metadata patterns across their user behavior. This playlist accumulates billions of streams annually and encourages users to explore beyond their existing likes. "Daily Mix" is a similar version of this music recommendation example. The user is given a blend of potentially new favorite music daily (Zhang et al., 2013). The regular updating of these curated playlists ensures comfortable and easy use of the app, reducing the exploration process significantly while encouraging more user engagement with the app because the search for new music is reduced to a simpler experience. Finally, Spotify Wrapped is a playlist of 100 songs that is provided by the end of each year, compiling the songs that got the most played by the user in the course of this year. Most recently, in December of December 2024, the newest edition of Spotify's Wrapped gained immense social media popularity on X, or short-form video platforms, partly because of the topic of AI and its presupposed controversiality. Users also started sharing how many minutes they have listened to certain songs or genres to compare with peers. For example, the X user ayeejuju posted: "so apparently spotify fired a lot of workers and used AI to create this year's

Wrapped, no wonder it sucks…" (ayeejuju, 2024). The post has since been viewed over 10 million times and reached over 350,000 likes as of 11 December. That Wrapped was made by AI here refers to the different sharable artworks and headlines such as "March was your chill-rock-ish-emo rap-phase," listing a user's top artists and listening minutes. The headlines are suspected to be AI-generated because they sound overly quirky and often do not make sense. A fact check disclaimer was added by X stating that AI is only used by Spotify for its DJ tools and that it is not confirmed whether employees' jobs have been cut and whether this has to do with AI integration. This disclaimer has since been removed. What can be speculated here is that while the job statement might be fake use, both users and the fact check disclaimer fail to recognize that by using the current task-based definition approach, AI is not only generative but is widely used for music recommendation.

SoundCloud adopted this platform model with the equivalents "Daily Drops," "Weekly Wave," and "Your 20xx Playback". The playlist can easily be shared across social media platforms or saved as such in the corresponding profile libraries.

Furthermore, many more playlists are curated by mood or time of the day, which SoundCloud also does. The integration of Last.fm tags and other user-generated data, the algorithms transform subjective, qualitative data into quantifiable acoustic features or genres. From activities such as workouts or study sessions, the streaming platform is able to provide playlists that fit the activities context (Biazzo & Farné, 2023).

Sodatone, the AI-driven platform for hit and talent detection, uses deep machine learning of datasets such as the MSD and various other data. While there is no proof of what the platform exactly uses, we can make assumptions that might fit. Sodatone potentially uses acoustic features such as duration, key, loudness, or danceability, which are all trained and defined by computer scientists. Machine learning algorithms such as support vector machines (SVMs), neural networks, or linear regression to classify songs by popularity, or rather, the potential of becoming popular, are likely applied (Ingham, 2018). Metadata that could be used are clicks, likes, social media presence, and activity, or the number of streams or views on platforms over a certain period of time. With genre classification, new songs can be compared to existing trends of what genres and tones are statistically likely to gradually change listener's preferences (Pham et al., 2015). Such an approach combines acoustic features and metadata to make accurate predictions that are expected to be trusted by labels and fans worldwide.

5.1.3 Spotify's Competitive Advantage

Spotify's capabilities in applying AI have likely contributed to its strategy of enhancing user engagement. Revenue is driven through increased ad exposure on the free tier and premium subscription. Spotify's AI-curated playlists have proven highly efficient in boosting user engagement. Users of the platform get the feeling of being understood by the platform they are interacting with. One critical factor is that the curation of playlists saves time while maximizing accurate output, making the app attractive to any user from a casual listener to the aspired DJ or producer that seeks inspiration or improvement of their repertoire. User loyalty and retention rates are boosted immensely by those factors (Chodos, 2019). Encouraging the transition of free users to paid subscriptions makes up a core component of Spotify's business model (Spotify Annual Report, 2023). Ad-free experience and higher sound quality create incentives to upgrade plans, resulting in higher revenue per user. The AI-driven recommendation system creates a premium experience that a user is willing to pay for when accessing the costs and benefits, thereby contributing to consistent financial growth (RIAA, 2023).

Spotify moved through the so-called algorithmic streaming phase taking place from 2014-2022 and paved its way for an era of centralized and platform-based streaming (van Dijck et al., 2019). The vast and, more importantly, early investments in AI form a competitive advantage over other platforms, such as Apple Music and YouTube Music, which also incorporate recommendations but have not achieved Spotify's level of personalization, either because they serve a different business niche, or specialize on other markets. Compared to SoundCloud, for example, Spotify serves a broader range of listeners. SoundCloud offers a vast catalog of music but has always been considered a more underground platform because it became popular mainly by offering the possibility to everyone, no matter their background, to upload audio. Soundcloud is targeted more towards a market niche for giving still-unknown musicians the possibility of uploading DJ mixes or music. For this reason, Spotify focuses more on popularity and major-label music distribution, ultimately reaching a broader and potentially more casual audience (Kearns, 2023). Spotify's consistent innovation in AI-driven recommendations and experimental features, such as AI-powered DJing, which offers spoken commentary between songs, exemplifies its commitment to constantly maximizing user experience and securing its market position (Kiberg & Spilker, 2023).

5.1.4 Ethical Considerations and Future Perspectives

As Spotify and other platforms or stakeholders within the music industry continue to integrate AI, several ethical issues emerge, particularly regarding data privacy, algorithmic bias, and the decentralization of content ownership. Additionally, the future of distribution technologies may be reshaped by blockchain and the emergence of Web3.0 (Taghdiri, 2020). Spotify's big data-driven recommendation system requires the acquisition, fostering, and analysis of a large amount of data, raising concerns about privacy. Critics might argue that Spotify's reliance on data mining situates it within the framework of surveillance capitalism, where user data is commodified on a mass scale to secure engagement and optimize revenue (Chodos, 2019). Although Spotify provides privacy control diligence that allows users to manage their data, this is likely only imposed to meet legal standards, which are minimal and often unable to keep up with swift technological changes. The increasing demand for personalized services pressures music streaming services to uphold transparency and ensure data protection more rigorously (Kiberg & Spilker, 2023). Spotify's use of CF and CBF can result in popularity bias or severe limitations to culturally diverse outputs, where mainstream music receives disproportionate attention at the great expense of niche genres and up-and-coming musicians struggling to make a living or gain online exposure (Hesmondhalgh et al., 2021). These biases risk creating a feedback loop, limiting diversity to the extent to which user discovery and the existing hierarchies within the industry are reinforced. Spotify has introduced mechanisms aiming to refine recommendations based on user feedback, such as liking or disliking content, by hiding it from the personal feed (IFPI, 2024). However, achieving genuine diversity in music discovery requires a much more comprehensive approach to algorithmic fairness and diversity safeguarding (Kiberg & Spilker, 2023).

As AI-driven personalization becomes the new standard, blockchain technology and Web3.0 offer a promising framework for reshaping the digital music ecosystem. Web3.0, due to its concept of decentralization, reduces reliance on centralized platforms like Spotify and could potentially offer users greater control over their personal data. Blockchain's distributed ledger technology could ensure greater transparency and enable artists to receive fair compensation for their creative work through direct, peer-to-peer transactions (O'Dair, 2019b; Ciriello et al., 2023). For example, Audius claims to empower artists by giving them control over their content and revenue through its decentralized setup. Built on blockchain technology, Audius seeks to eliminate intermediaries to the best of its ability, allowing artists to distribute music directly to fans and get paid in an entirely transparent nature. Its self-developed $AUDIO crypto-tokens were founded for the purposes of governance, access, and incentivizing network participation. Furthermore, Audius offers decentralized content storage, digital asset encryption, and a community-driven infrastructure. Audius is an open ecosystem in which artists, fans, and node operators collectively enhance the platform's success (Rumburg et al., 2020) and could shape a promising future in the music landscape.

5.1.5 Final Remarks

While AI integration in music streaming has brought economic benefits, we can conclude that it has not yet sparked a fundamental paradigm shift in the industry. Streaming platforms like Spotify consistently raise revenue and user numbers. However, as noted, streaming potentiates an extreme and fast-paced digital commodification of music, making it a functional aspect of daily life rather than an immersive experience (Hesmondhalgh, 2021).

This rapid commodification has both advantages and disadvantages. On the positive side, it boosts democratization levels of music discovery, allowing users to access an expansive music catalog that they might not encounter otherwise, or if they do, they would need a lot more time and effort or even professional expertise in music repertoire curation. Accessibility can broaden the reach of artists. However, one crucial downside is that music becomes a mass-consumed good that caters to passive listening. This leads to, e.g., songs becoming increasingly shorter in both creation and duration. User engagement on the platform is boosted, but on the flip side, the engagement with the artwork itself is reduced (Ibid.). In the context of Sodatone and Spotify, one has to remember that every platform in a sociocultural digital arena communicates and works with each other. Going even further, a hit song detector such as Sodatone and a digital distribution platform such as Spotify are both built on AI and do thus not only indirectly collaborate with each other but directly *learn* from each other in real-time. This could lead to biases and loops by the human-independent machine-to-machine relationship, posing imminent threats to plurality. On a positive note, however, whether this profoundly affects user satisfaction will remain open for debate and should be the subject of future academic investigation.

Ultimately, while exceptionally lucrative, these factors shift art appreciation more towards quantity over quality or creative depth, constituting both the global and innovative progress and the pitfalls of music culture at the same time. As for the often presupposed dichotomy in discourse about AI, that AI either helps or limits, collaborates or steals authenticity and jobs, however, in the context of applications such as Sodatone, it can be argued that it does not take away the job of an A&R talent scout. Instead, it takes away part of the workload, leaving more time and resources to the human performer. The same argument applies to streaming since it is ultimately the consumer's preference whether quantity or quality is valued more than the other. The sheer fact that streaming technology advances does not seem to take away this freedom of choice per se.

5.2 The Case of Music Production

5.2.1 AI Assistance in Digital Music Production

The integration of AI in music production led to new groundbreaking possibilities for artists and producers. It can be argued that AI is currently revolutionizing how music is composed and edited or where musicians grab their inspiration from. The following paragraphs will list three AI tools: Sony's Flow Machines, Google's Magenta Studio, and the Izotope Ozone. The choice covers two crucial processes in music composition, namely the generation of melodies and harmonies and the music engineering phase of final polishing of a musical piece, mastering. The tools, along with many other generative and non-generative assisting apps, make part of a transformative movement in technological music innovation. Human creativity is enhanced, but as we have already seen in the literature, this can only come with the challenging of traditional concepts of authorship, creativity, authenticity, and music ethics (Goldmedia et al., 2024). This chapter briefly describes each tool's functionality and then discusses notions of an effective human-machine relationship and ethical concerns (Tillmann & Zaddach, 2024). Once again, the potential in Web3.0 and blockchain technology is touched upon, and concluding remarks are provided.

5.2.2 Industry Facts

A recent large-scale study conducted by Goldmedia for GEMA and SACEM (2024) states important key facts about AI in music, and the ecosystem. It is useful to take a look at some of their findings.

The study surveyed over 15.000 GEMA and SACEM members, including authors, artists, publishers, and other music industry experts. Firstly, the global generative AI market for music reached $300 million in 2023, which constitutes around 8% of the entire generative AI market worth $3.7 billion. It is expected to grow to 60% with a share of $3.1 billion by 2028. Regarding the factor of growth, these are exceptional numbers. Additionally, Europe's investment in AI technology surpassed $50 billion, with Germany and France making up $16 and $12 billion, respectively. Amongst music creators, 36% used AI in their art. AI usage is more common in artists under the age of 35. About 64% of participants reported not having used AI in their productions, while 13% rank under potential users in the future, and 19% are hardline rejects of using AI anytime soon. When asked about potential areas of adoption of AI, 63% estimate that AI will primarily be used in composition and text-writing, 58% think AI will see big adoption scales in recording, editing, and mixing of music, or in other words, mastering, and 55% estimate it to be prevalent in promoting content.

On a more negatively loaded side, AI could lead to a 27% revenue loss for music creators by 2028 due to the potential replacement of human-made content. However, this can be argued to be a vague prognosis that might not hold up because it is dependent on too many complex factors, such as the success of fully automated human-independent AI production. Finally, the most striking result of the survey, by a great margin, regards the assessment of opportunities and risks of AI in music by the surveyed participants. When asked, "All in all, do you think the opportunities outweigh the risks when it comes to AI in music and creation in general, or do the risks outweigh the opportunities?". A striking 94% answered that the risks outweigh the opportunities, while only 2% think the opposite. The remaining 4% think they are about the same (Goldmedia, 2024). This is a highly significant outcome and suggests that there might be hard skepticism toward AI use among creators.

5.2.3 Flow Machines, Magenta Studio, and iZotope Ozone

Flow Machines was developed by Sony Computer Science Laboratories Inc. (Sony CSL) and is a notable AI-driven composition tool in contemporary digital music production (Knotts & Collins, 2024). Designed to generate new compositions, it uses machine learning based on already existing styles to analyze patterns in data from multiple genres and eras (Sony, n.d.). For example, Flow Machines was used to generate "Daddy's Car," a Beatles-inspired track showcasing the generative capabilities of AI and its stylistic nuances by using deep learning techniques. (Flow Machines, 2016). Flow Machines can be considered a co-creative assisting tool that is able to provide prewritten melodic notations, which the human creator can then elaborate on. Thus, computational creativity is fused with human cognitive intuition (Gioti, 2021).

Google's Magenta Studio is a compilation of plugins that use deep learning techniques to assist in the generation of drum loops, melodies, or synth MIDI notations. Unlike Flow Machines, which are based on a compositional framework, Magenta Studio works in real-time within DAWs such as Ableton (Hawthorne, 2017). Magenta employs RNNs and LSTMs, which lets users iterate music ideas. The experimentation process is enhanced by providing immediate feedback to the user. Therefore, the tool aids in having artists develop ideas that may not have come from traditional AI-less composition (Bohm et al., 2023).

IZotope's Ozone 11 is a software that has AI integration in sound mastering. Ozone analyzes audio files or the DAW's ongoing project to suggest EQ settings, compression, or other filtering adjustments of the sound that are tailored to a particular sound profile. Mastering an unfinished piece of music is a laborious process in which sound engineering expertise is necessary. Ozone's AI-driven approach not only speed up the workflow but also enables the artist, who might not be a sound engineering professional, to master his creations. The software provides precision tuning, which boosts unmixed sound quality to studio quality while having learned to keep the entire sound character of the musical piece (Stewart, 2023). This makes it especially attractive among independent musicians or smaller record studios, making professional-level mastering significantly more accessible to amateur song-mastering artists (Rickard, 2022).

5.2.4 Thoughts on the Human-Machine Relationship

It can be argued that all three tools do not replace human creativity but serve as collaborators that expand the musician's creative palette. Each of these tools enhances different aspects of the production process. First, Flow Machines primarily assists in ideation when generating structural frameworks as helpers, Magenta Studio introduces new rhythmic or harmonic possibilities, and Ozone, at least partly, automates professional mastering adjustments, which gives creators more room for creative freedom simply because they have more time on their hands (Bohm et al., 2023). Understanding AI as a partner and using AI to "stumble" upon initially unwanted moves in the production process both speak for a collaborative scope; the artist's inspirational horizons are broadened since triggering unwanted actions, or mistakes in the compositional process, is an inherently human trait that can never be impeded by soft- or hardware. Following this argumentation and acknowledging the complexity of creative art processes as the foundation of a possible differentiation between AI music and non-AI music, if there can ever be one, that a shift toward more emphasis on aesthetic sound design rather than skepticism toward AI usage will be caused, becomes more likely. (Tillmann & Zaddach, 2024).

This acceptance of AI in music production opens new possibilities for distributed forms of collaboration between a human agent and a machine, for why should one assume creativity, which follows from learning and adapting, to be diminished when it is restructured? AI does not dictate creative choices, in the context of music production, it is never fully autonomous. The main goal of professional music producers is to create a synergy between machine assistance and human creativity for artistic innovation. There is no reason for an artist to restrict their own authentic creativity. Because MIDI manipulation tools such as Ableton's Magenta Studio work through neural network machine learning, making the point that AI assistance is immoral or detrimental to "true" and authentic creativity comes close to claiming that working together as a band is not creative due to the reason that the art is a group product and not the work of a single individual. Because this is an illogical statement, it can be argued that it is categorically false to assume that collaboration, whether human-to-human or human-to-machine collaboration, is uncreative.

As M. Gioti (2021) notes, AI is a second agent that pushes artists to expand their creative range without infringing their creativity, which ultimately counts. Shared creativity is not less overall creativity unless one finds a method to quantify creativity and make a harsh distinction between human and non-human creativity by unconditionally tying it to the existence and degree of intellectual property ownership. When we presuppose that a musical process is less creative because a highly intelligent machine was used, we also assume that creativity is reduced because the human agent does not own the creation anymore. One would have to argue that it is possible to attribute intellectual property ownership to a machine, which, at least by today's standards, results in a logical fallacy. The skeptic, therefore, attributes more "humanness" to the machine than the AI optimist. The same goes for the fact that no one would claim that one song is less creative than another simply because it was produced by two instead of one artist. Whether AI is seen as a tool or as an autonomous creative agent when critiquing creativity as an artistic concept is irrelevant, for neither do we question the degree of creativity solely due to the use of an instrument nor due to the fact that art creation is the result of a collaboration between multiple people.

Inherently, the human-machine relationship has always been a symbiotic cooperation. Where AI serves as a tool that accelerates workflow but also enriches experimentation and exploration in ways that are beyond conservative musical structures, the process of music creation is expanded. (Braguinski, 2024)

5.2.5 Creative Authenticity and Ethical Implications

The issue of authenticity in AI-generated music remains a complex one. When Flow Machines co-authored "Daddy's Car," for instance, the line between human and machine authorship became blurred because traditional notions of ownership and originality in music were challenged. Authorship disputes have come up around AI-composed music, with creators questioning if AI-driven productions should be attributed to the human artist, the developers or owners of the software, or even the (intelligent) machine itself. According to Zaddach, this ambiguity raises drastic concerns in the music community, where creators fear the diminishing recognition of human effort (Tillmann & Zaddach, 2024). On the flip side, in terms of the autonomy of the artist vs. the autonomy of the machine, as long as AI is supposed to fit into specific genres, the artist's input and professional knowledge, as well as creative vision, will always be needed (Ibid.). It can be argued that the notion of degree of autonomy of a computer system and the authenticity of the created art piece are entirely distinct from what instruments or tools are used because they are in practice nothing more than technological assistance. Following this line of argument, judging the exact degree of autonomy in the creative process might objectively prove to be neither possible nor relevant. N. Bohm et al. in "Evaluating AI as an Assisting Tool to Create Electronic Dance Music" support this by finding that AI assistance significantly sped up and enhanced the production process and that AI assistance of a non-generative nature, so with little machine autonomy, is not detectable to the average listener (Bohm et al., 2021).

The introduction of AI into music creation certainly moves ethical and legal problems related to copyright to the spotlight. As AI tools often use datasets comprising existing music, concerns arise over the originality of AI-generated outputs and the potential misuse of copyrighted material or personal information that is used without permission. Furthermore, the GEMA study emphasizes that generative AI's application severely impacts musicians' livelihoods. Particularly if AI systems bypass traditional compensation models and streaming service over-commodification continues to keep earnings low (Goldmedia, 2024). Last decade, we saw a call for new legal frameworks that credit human creators appropriately and have clear guidelines about AI's role and consumer or creator rights within the industry (Dolata, 2011).

Many scholars, such as Stammer (2023) or Sturm (2019), highlight the fact that the debate around ethics and copyright issues is not new. However, with swift advancements in the sophistication of generative AI and their qualitative outputs, the lines between computer generation and human creativity make ethical and legal demarcations increasingly intertwined (Stammer, 2023). Copyright, as it is defined today, presupposes a human legal person as an intellectual creator. The controversy, therefore, lies in the fact that an AI system can be considered as having creative generative skills that would then imply ownership. Legally, the AI remains a technical instrument even though it has been trained with massive amounts of human-made data to perform. This raises two main legal questions: Who does the computer generated content belong to if neither to the human producer nor the AI tool programmer/provider? And secondly, what copyrights can be claimed by the thousands of creators of the datasets used to train an AI system, if any? One deciding factor then seems to be how much creative ability can be attributed to the human or the AI system in question (Kitzberger, 2023). Stammer (2023) lists four guideline principles informed by UK Music, Human Artistry Campaign, Independent Music Publishers International Forum, and CISAC: Firstly, copyright holders must be asked for permission when their music is used to train machine learning systems. While this sounds reasonable and necessary in theory, in practical reality, asking thousands, if not millions, of copyright holders if their data can be used to train software seems impossible. The same logic applies to the second principle, that there needs to be transparency in what creations have been used to train machine learning systems. Third, works that have been entirely AI-generated shall be directly indicated as such. This principle, again, is reasonable and logical; however, works that are entirely, without exception, made only by an AI system are simply non-existent. Furthermore, it is highly questionable who and how this ought to be measured and by what specific guidelines. Lastly, in the context of deep fakes generated with AI, the intellectual property rights of the imitated artist shall be respected. Contrary to what is the case with the other three principles, this can and should be practically executable.

Considering that legally these issues have been discussed over decades, the mere fact that generative AI is now gaining exposure in many discussions does not provide enough reason to claim that we do not have the proper legal frameworks or laws to deal with arising issues. Rather, the field of intellectual property in the music industry might need more expertise or manpower in legal prosecution and the execution of strict principles. Additionally, ethical sentiment pertaining to how we think about authenticity and creativity that is assisted or shared technologically might, as a long-term reaction, loosen up significantly in the years to come because the mentioned principles might end up being impossible to execute in practice. As we have already seen in various sources, another ethical implication that needs to be discussed is the cultural bias in the training of both generative production tools and music recommendation systems, which repeatedly have been proven to be biased towards Western cultural music, priming the market towards this cultural sphere (Holzapfel et al., 2018; Stammer, 2023). In terms of sustainability and eco-friendliness, Stammer suggests that the quality of already existing AI tools should be measured by this factor, and instead of programming new tools, existing tools should be improved. Born et al. (2021) propose a culture-centric model of optimization to emphasize balancing economic efficiency with the promotion of cultural diversity, inclusivity, and plurality. The development of regulatory frameworks or the enhancement of existing guidelines has to ensure transparency, fairness, and accountability in AI integration across all domains regarding distribution, creation, and profit-driven labor market dynamics.

5.2.6 Future Perspectives: AI, Blockchain, and Decentralization

AI technology in music production will likely advance in complexity, providing even more sophisticated generative options that include real-time music composition. As AI systems become more integrated into the creative process, artists may increasingly adopt them as essential elements of their toolkit, which, in the long term, redefines what it means to be a composer or producer in the digital age. Yet, as Braguinski (2024) suggests, this shift requires a vast range of skills and a recalibration of human expertise to complement AI's role in the industry.

Blockchain technology and Web3.0 frameworks have the potential to transform music distribution and intellectual property management. Blockchain technology offers a decentralized method that can ensure transparency and security in music transactions, allowing artists to protect their rights without relying on centralized agencies. Cases such as Napster's acquisition of Mint Songs signify a shift toward a more democratized music ecosystem (Dalugdug, 2023). This signifies a potential to move from the current heavily platformized streaming network to be able to lend or at least partly "own" songs again. NFTs, representing unique digital assets, could be tied to AI-generated music, giving artists more control over royalties and intellectual property (Stammer, 2023). However, this is still too novel of a development for one to be seriously expecting a groundbreaking change in the near future.

6 Concluding Remarks & Discussion

This paper has explored the role of AI in the music industry by identifying the AI tools used in the digital distribution and creation of music. The current state of the art has been described, and the academic evolution regarding the two studied themes has been reviewed. Lastly, we zoomed into two case examples for each of the two themes and identified and discussed challenges that come with the integration of AI and its swiftly developing innovation.

AI tools in the music distribution sector deep learning machine algorithms that use complex hybrid filtering and neural network models to recommend music to streaming platform users based on listening behavior and context. These systems are programmed APIs of the corresponding music streaming provider and are therefore not clearly defined and depend on the definitional scope of what the observer deems to be AI. Following the broad task-based definition applied in this paper, the use of AI can be found in the app interfaces whenever complex algorithmic programming becomes apparent in playlist curation. In music creation, we can distinguish between descriptive and generative AI tools. There are more than twenty popular tools that can be used by both amateurs and professional artists and sound engineers. Contrary to AI integration in music recommendation, music creation tools can be clearly labeled, sold, and used as AI tools, which therefore simplifies the accurate categorization of these software.

Academic research on AI in music has evolved from foundational explorations of recommender systems to more complex analyses of generative AI and ethical perspectives in music production. Additionally, recent studies expanded into sociocultural, economic, and cultural topics reflecting AI's growing influence on society as a sociotechnical phenomenon. We can reasonably conclude that AI has rapidly advanced to be a new standard in music distribution and creation and is not an inherently new exceptional technology marking a paradigm shift. Whether an unequivocal paradigm shift occurs, for example, with AI technologies becoming even more autonomous, depends on the practical circumstances of how biases or copyright issues are dealt with in normative practice. A groundbreaking reform and a full digitalization and adoption of infrastructures such as Web3.0 and blockchain can help catalyze this potential. Democratized and user-centric balancing of for-profit innovation plays a crucial role.

The integration of AI technology in the music industry, spanning from streaming and distribution to production and creative processes, is an unavoidable progression with no sign of stopping anytime soon. AI advancements are proving themselves to be indispensable tools, changing the ways in which music is created and consumed. Despite reasonable challenges, no stakeholder shows an incentive to halt or resist this groundbreaking change. There is enough reason to believe that, at the moment, there is no incentive convincing enough to go against the use of AI. Therefore, academic research and laypeople who shape public opinion need to deal with the effects that impact their respective situations. The discussion around AI in music cannot be isolated to single application areas; it is not a standalone matter. AI tools in distribution, as seen with Spotify, and AI in creation, in the form of generative or descriptive AI, are highly interconnected and, as intelligent computer systems, quite literally learn from each other. While ongoing scholarly research on AI in music is robust and compelling, it often separates its areas of application into distinct studies, which does little justice to the complexity of the matter. This paper opted to provide an explorative review and an insight into practical situations to synthesize what we can draw from a holistic perspective. Both areas share similar challenges of bias and ethical or legal concerns that come with AI integration.

Ultimately, within both areas, it is the consumer who will determine the trajectory of these innovations and their power to create paradigm shifts or advancements big enough to end in structural changes. Listening to music is a phenomenological and subjective experience, and thus, the end consumer is somewhat indifferent to the technical details of AI algorithms and data processes. What cannot be overlooked is that consumers' preferences and the wish for rapid and effortless convenience, quality, and variety will most likely dictate how AI continues to evolve within this industry. Many intellectually important factors remain largely behind the scenes and debates surrounding them are subject to gatekeeping or business non-disclosure. Additionally, while blockchain technology and Web3.0 visions are tolerably promising, their large-scale adoption remains uncertain. Their potential depends not only on technological feasibility but also, yet again, on consumer willingness and readiness to engage with blockchain-based systems so that these technologies do not remain niche gimmicks. Currently, those visionary proto-technologies are still reserved for those well-versed in cryptocurrency, NFT, and new computer science trends.

The literature repeatedly proves that AI has become integral to the music industry. Stakeholders and creators, no matter their exposure levels, must approach its adoption with a balanced and reserved perspective, ensuring ethical safeguards and user control while this swift technological change occurs. Whether in distribution, production, or legal fields, AI's real potential lies not in replacing human creativity and work but in enhancing it, creating a future where technology and artistry coexist in a redefined digital music landscape. To spark this potential fully, the main concerns are how we go about the reception and seamless acceptance of AI. Music, just like any art form, will always depend on how it is consumed, by whom, and for what reason.

A specific dichotomy can be derived from the interplay of distribution and composition AI: artists and listeners might have to face a new reality in which music is created to be *streamable* vs. culturally expressive, meaning that a decisive amount of control is given to the distribution economy. Practical and ethical or philosophical challenges can and should be discussed in the light of what can be called *streamability*. New technological innovation in the modern music industry may, therefore, increasingly be put in the controversial spotlight for good reason. While media hype seems to primarily focus on the power of novel AI music generation, awareness should be raised about the fact that the phenomenon of AI in distribution and creation is a closed, constantly evolving, and internally reinforcing system that is inseparably twofold and symbiotic.

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