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Music and Affectivity in the Age of Artificial Intelligence

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Abstract

Music and affects share a long history. In recent times, 4E cognitive sciences (embodied, embedded, enacted, and extended), situated affectivity, and related ecological theoretical frameworks have been conceptualizing music as a case of a tool for feeling. Drawing on this debate, I propose to further theorize the role of music in situating our affectivity by analyzing how the very affective affordances of music are technologically situated. In other words, I propose to shift the attention from music as a tool for feeling to the tools for feeling music. I argue that the experience of music as a tool for feeling may be altered, enhanced, or lessened depending on the tools for feeling music. I investigate the extent to which AI might be a case of a tool for feeling music and examine the influence it could exert over musical affectivity. I conclude that AI can be considered a tool for feeling music of curatorial type and that the limitations and/or biases of AI as a method risk lessening the power of musical affective affordances.

Keywords Musical affective affordances · Situated affectivity · Music streaming · Music recommendation · Music curation

1 Introduction

The historical connection between music and affects (or emotions)[1] is well-established. However, philosophical and scientific disagreements start when one tries to determine the nature and scope of that relation (e.g., Juslin and Sloboda 2011). In this paper, I will adopt as a first premise the thesis according to which music is used by listeners to modulate their emotions (Krueger 2011, 2014, 2019). It is not my objective to defend the universality of that definition, nor do I aim to defend it against alternative approaches explaining the relationship between music and affects[2]. My presupposition is simply that, at least some music in some cultures is used by some listeners to modulate their emotions. If one accepts this premise, the framework of situated affectivity (Colombetti 2014) emerges as an intuitive approach to further analyze that potential of music. Following this line of thought, music can be described as a popular *tool for feeling* that enables listeners to engage with a vast array of affective experiences (Piredda 2020; p. 553).

The digitalization of music and the massive popularization of music streaming platforms powered by data sciences and artificial intelligence (AI) may be reshaping how listeners employ music to regulate their emotions. Scholars have already argued that music streaming platforms have disrupted and revolutionized the music industry on a global scale (Cook et al. 2019). Furthermore, it is already known that these technologies raise significant economic and ethical

[1] One could also include notions such as feelings and sensations here. In this paper, for the sake of simplification and consistency, I will use the terms affects and emotions interchangeably. As was already clarified by Colombetti, the scientific approach to affectivity, which will be addressed in this paper, is interested in a wide range of phenomena, "[…] such as emotions, feelings, moods, and mood disorders." (Colombetti 2014; p. xiii).

[2] For example: the greek theory of *musical ethos*, particularly its Aristotelian version (Anderson 1966); the *doctrine of the affections* (*Affektenlehre*), which refers to multiple perspectives introduced by philosophers and musicologists in the eighteenth century (Buelow 1983); the foundational musicological work of Eduard Hanslick *On the Musically Beautiful* (Hanslick 1854); Susane Langer's philosophical theory of music as a knowledge of human feelings (Langer 1957; p. 179); and the famous psychological approach introduced in *Emotion and Meaning in Music* by Meyer (1956).

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concerns (Hesmondhalgh et al. 2023). However, little attention has been given to the fact that many of these services promise to deliver musical products such as curated playlists and soundscapes, *capable of eliciting specific affective responses in listeners* (e.g., Spotify, YouTube, Endel, Brain.fm, Enophone). Researchers already speculate that technological advances in data sciences and AI could revolutionize the use of music as a tool for feeling (e.g., McGroarty 2020; Haruvi et al. 2022). For instance, in a seminal paper, Greenberg and Rentfrow (2017) argued that the availability of vast amounts of data on songs, consumption behaviors, and even on physiological responses to music will inspire new insights about musical affectivity, eventually leading to new music-based services and ultimately impacting the way music is used by millions of people to regulate their emotions.

That being said, in this paper, I propose to analyze whether the use of AI to curate music with the aim of eliciting affective experiences is re-situating musical affectivity and, if this is the case, what the implications of this new scenario could be[3]. Is it possible that this shift towards AI-based musical curation could enhance, lessen, or transform music's capacity to modulate our emotions? And, if so, how and why does this occur?

Here is the summary of the argument I will develop in the next sections: After introducing the notion of musical affective affordances to better explain how music works as a tool for feeling (Sect. 2), I will argue that we also need to consider the tools for feeling music – contextual variables capable of altering, enhancing, or lessening music's capacity to modulate our emotions (Sect. 3). I will contend that curation is an example of a tool for feeling music. Then, I will show *that* AI is being employed to curate music with the objective of generating playlists tailored to elicit affective experiences in listeners; therefore, AI can be considered a new type of tool for feeling music (Sect. 4). I explain *how* AI is employed in these cases, asserting that AI operates a shift from musical affective affordances to numerical representations of them (features). Finally, I outline a map of potential negative consequences of the shift from human-based to AI-based curation of musical affectivity (Sect. 5).

2 Music as a Tool for Feeling

The notion of 'tool for feeling', like 'tool for thinking' and 'tool for acting', is part of a broader framework that investigates the relationships between material artifacts and embodied minds (cf. Heersmink 2021). As explained by Viola (2022), this notion refers to objects or artifacts that "enable, foster, or maintain some affective feeling" (Viola 2022, p. 2), and also to those "artifacts that exert a *negative* influence on some aspect of our affective life, inhibiting or dampening some affective states" (Viola 2022, p. 2, emphasis in the original). In the literature on situated affectivity, music is one of the many examples of the so-called tools for feeling. As summarized by Piredda (2020; p. 553), music allows us "to express our moods and emotions, and to modulate or regulate them" (Piredda 2020; p. 553).

To further explain *how* music can function as a tool for feeling, Krueger (2011, 2014, 2019) has developed the notion of musical affordances, which I will adopt in this paper. Two reasons motivate this choice. First, unlike other approaches to musical emotions (cf. Budd 2022), Krueger's notion of musical affordances was conceived within the framework of situated affectivity and therefore it can be more easily incorporated into my proposal. Secondly, and more importantly, I will argue in Sect. 4 that there seems to be a clear parallel between the notion of musical affordances and the notion of musical features used in the literature on AI and music. At this point, the notion of musical affordances will reveal its epistemic fruitfulness to tackle the topics here discussed.

For now, let us understand what musical affordances are and how they relate to music as a tool for feeling. Building upon Gibson's famous notion of affordance (Gibson 1979), Krueger (2014) undertakes an analysis of what music affords the listener, what the structures of these affordances are, and how they are phenomenologically experienced. He concludes that one of the things that music affords is *affective synchronization*. In other words, listeners allow music to regulate their emotional states (Krueger 2014). Thus, we can say that music contains musical *affective* affordances[4], serving as an "'esthetic technology' to enact micro-practices of emotion regulation" (Krueger 2011; p. 1).

According to Krueger, music is capable of affording affective synchronization *by virtue of its acoustic elements structured in such and such ways and in relation to individuals capable of grasping them* (Krueger 2011; p. 5). Therefore, he defends that musical affordances are of an *interactional* nature, i.e., they are properties of the listener-music relation (Krueger 2011; pp. 4–5).

From the perspective of the listener, examples of musical affective affordances are melodies, rhythmic patterns, guitar riffs, and grooves. However, musical affective affordances can range from simple units to highly complex multilayered

[3] In further research, the same questions should be applied to the case of AI-generated music and soundscapes. For now, I will focus on the case of curation of existing music.

[4] Note that Krueger does not claim that music contains only affective affordances. On the contrary, he argues that music also affords, for example, sensorimotor responses and bodily entrainment (Krueger 2014). But for the sake of this paper, my focus will be on the affective affordances.

structures. A very dissonant interval played with a simple constant rhythm might elicit the feeling of tension, like in the famous soundtrack of the movie *Psycho*. A melodic orchestral line in a minor key might afford the experience of melancholy, as heard in the well-known theme of the movie *The Godfather*, while a march-like melody in a major key might evoke the experience of an epic upbeat emotion, as in the main title of *Star Wars*. Obviously, these are merely illustrations of how musical affective affordances might 'look like', so to speak. Phenomenologically, listeners might grasp basic unities such as an interval, but also very complex structures, such as a rhythmic-harmonic-melodic pattern unfolding in time. In any case, these affordances are structures contained in the musical piece that are capable of suggesting, inclining, enabling, evoking affective experiences in the listener able to grasp them[5].

Hence, Krueger concludes that "[m]usical affordances thus emerge through the dynamic, temporally extended interaction between active listener and musical piece. They are realized within this relation" (Krueger 2011; p. 5). I believe, however, that we have to expand on this definition to acknowledge the important role played by *technology* in this interaction. Thus, building on Krueger's account of musical affordances, I propose the following definition: musical affective affordances emerge through dynamic, temporally extended, *and technologically situated* interactions between active listeners and musical pieces. That conclusion points to the overlooked role played by the tools for feeling music.

3 From Music as a Tool for Feeling to the Tools for Feeling Music

I propose to shift the emphasis from the musical affective affordances to the tools that enhance or even enable those affordances in the first place. Thus, a shift from music as a tool for feeling to the tools for feeling music. Note that these frameworks are not opposites. In the latter, music continues to be understood as a tool for feeling, it continues to be a phenomenon full of affective affordances that situate, regulate, not to say extend, one's affectivity (cf. Krueger 2014). It is only a matter of emphasis. What I propose to further theorize is the role played by variables outside the acoustic affordances present in a song in how this song or musical piece will alter "the affective condition of an agent" (cf. Piredda 2020; p. 554). In other words, the target of my inquiry is the extent and manner in which the material context or situation influences, enables, enhances, maintains, lessens, disperses, transforms musical affective affordances. By understanding the situatedness of musical affective affordances, we should be able to gain novel insights into how AI might be re-situating musical affectivity.

3.1 Tools for Feeling Music

Previous authors have already addressed the topic of tools for feeling music, though not in the context of situated affectivity. In a pioneering postphenomenological approach to music, Flusser (2014) argues that listening to music depends not only on the song one listens to, i.e., its intrinsic acoustic/musical features or the musical 'content', but also on the 'channel', for example whether the piece is being listened to via television or vinyl (Flusser 2014; p. 112). In the postphenomenological tradition, we could also mention Ihde's analysis of the impact of electronic technologies on listeners' sensibilities in the twentieth century (Ihde 2007; p. 227–233). In his seminal ecological approach to music perception, Clarke (2005) made an extensive critique of the idea that musical emotions can be reduced to the "world of the work", i.e., the idea that "specific emotions are conveyed, or triggered, by particular musical procedures" (Clarke 2005; p. 175). According to him, the affectivity of music is experienced on a much wider, heterogeneous, and heteronomous scale which includes, for example, the experience of physicality and agency of the instrumentalists, acoustic textures, movements and virtual spaces that are much more ecologically situated than the "world of the work" could account for. In similar vein, Krueger (2011; p. 16) has suggested that our listening experience is often socially specified. After analyzing the example of attending to live concerts and the phenomenon of joint attention, Krueger concludes that "the music within that social context is given differently, in an experiential sense, than when listening to that same music alone." (Krueger 2011; pp. 17 – 8).

Other specific examples of tools for feeling music that could be mentioned to further clarify this notion are notations, visualizations, texts, gestures, and other sorts of technological media. My hypothesis is that, just like in the phenomenon of jointly listening to music, artifacts that mediate how music is accessed also influence the listener's attention, directing it to certain aspects of the musical piece, highlighting them, and eventually pushing other aspects to the background. In that sense, I would argue that *media is capable of impinging on the affective affordances contained in a musical piece*. For instance, gestures can enhance the power of certain affective affordances by directly pointing at

[5] As mentioned before, the 'realization' of an affective affordance is not immediate. It also depends on the listener. Variables that mediate this process range from physiological disposition (e.g., certain levels of hearing loss or something like tone-deafness certainly impact this process) all the way up to cognitive capacity, habits, previous experiences with the repertoire, cultural constructs, and so on. These are all variables that will determine whether and to which extent certain musical affective affordances will be grasped and thus 'realized'.

them, like conductors do. Notations, not only the traditional score but also other forms of visualization, can enhance musical affectivity by drawing one's visual attention to certain affordances contained in the piece. In sum, media has the power to make musical affective affordances more available to the listener and/or to make the listener's attention and sensibility more available to those affordances.

3.2 Curation as a Tool for Feeling Music

Curation[6] is another example of tools for feeling music. In fact, it is a highly overlooked form of tool for feeling music. Though little attention has been paid to this form of mediation in studies on music and affectivity, it is easy to attest that curation has been a central element in the 20th and 21st -century popular music cultures (cf. Tessler 2021). For example, for decades people have been curating music to set the mood for special occasions (e.g., a party or an intimate dinner) and to cultivate personal memories and relationships (e.g., the famous personal mixtapes exchanged between lovers and between friends). The figure of the performing DJ, the culture of turntablism, the widespread influence of radio in the past century are also examples of how interconnected musical affectivity and curation have been. Such cases reinforce that music is a very popular tool for feeling; but they also indicate that curation is a special type of tool for feeling music.

Curation is deeply entangled with the various technological media used to record (vinyl, tapes, digital) and transmit (radio, Internet) music. My claim is that, like visualization or notation and other media, curation can also impact the experience of musical affective affordances. For starters, many practices of curation, and namely DJing, intentionally explore musical affective affordances[7]. That is to say: the person curating a setlist will have an affective goal in mind, certain emotional or affective states, e.g., some mood, that one wishes to install with the help of the right music. To achieve that goal, they will have to identify in the catalogue available to them those songs that contain the adequate affective affordances – the right grooves, melodies, timbres, and so on. Then, songs will have to be arranged in a certain order – perhaps even mixed, like when only parts of each song are played – to enhance their capacity to elicit or induce the desired affective state.

Now, those two operations – selection and ordering of musical affective affordances – can be relatively easy and straightforward if one aims at basic or superficial affective experiences. A setlist with merely 'background music' could illustrate this point. Another example could be if one is interested in songs that contain very specific and simple features, e.g., distorted guitars, Latin rhythms, or piano sounds. In those cases, though the curation engages with musical affective affordances, the act of curating music per se might not really have the power to, say, enhance or transform the affective power of those affordances. In fact, a simplistic curation might even lessen the affective power of some of the songs selected. If experienced separately, they might have been more powerful than in a bad mix.

However, things become enormously more complicated when we consider the case of 'experts', such as great DJs or radio hosts or even amateurs that end up being great musical curators. In such cases, the affective states aimed at will likely be much more complex and intense than more basic experiences such as those elicited by a generic playlist with piano music, for instance. And to reach such levels of affective complexity and intensity, curators will, for instance, select and order/mix musical affective affordances in unusual ways, thus altering and/or enhancing the power of the songs chosen. For example, by ordering songs with certain changes in tempo or harmony, or by paring grooves from genres that are not often experienced together – by doing such acts of curation, one can change and eventually uplift music's capacity to modulate our emotions. In those cases, it should be possible to differentiate the affective power of the songs when listened to individually or in other contexts vs. the same song as it appears at some point in some specially curated setlist.

Nowadays, in the age of streaming, people no longer design personalized mixtapes and radio DJs and curators do not have the same importance as they used to have in the 20th century. However, music curation continues to play a central role in how popular music is experienced worldwide (Barna 2017). It is easy to attest that music streaming platforms offer various types of curated playlists to their subscribes. Moreover, many of those playlists are curated with the intentional goal of eliciting, inducing, or at least suiting specific affective states in/of their listeners. Given the ever-growing role played by AI algorithms in those platforms,

[6] For an updated overview on the notion of curation in music, see Jansson and Hracs (2018).

[7] The relationship between DJing, curation, and musical affectivity has not been systematically explored yet. However, besides commonsense knowledge of that relationship, I would quote, for the sake of reference, the following passages. In a study on musical education, scholar Sloboda (2001) defines DJing techno music as follows: "The music is constructed in real time out of computer-manipulated elements at the disposal of a DJ. Its primary function is to support communal (but individualistic) dancing designed to induce certain altered states of awareness." (Sloboda 2011, pp. 248-9). More clarifying, however, are the following words from a blog post by a practicing DJ in which we read: "A human DJ will always have one thing that AI will not, and that is feelings. […] we attach ourselves so deeply to the music because of our own personal experiences. […] This is why human DJs are important. A true sound curator knows how to tap into those feelings and stories, and weave them to connect the masses. […]" (DJ Waves, 2019, available in: https://www.djwaves.ca/blog/blog-post-title-two-pbdpx. Retrieved Feb 14 2024).

it is important to ask to what extent the use of AI to curate music might be re-situating musical affectivity and what could be the implications of this new mediator for listeners. Is AI a new tool for feeling music? And if so, how is it different from human curators? What can we expect in terms of musical affectivity from this shift from human curation to AI curation?

4 Artificial Intelligence as a Tool for Feeling Music

In this section, I demonstrate that AI is being employed to (partially) automate music curation, and that AI is being employed to (partially) automate the curation of musical affectivity more specifically. In this sense, it will be argued that AI constitutes a new tool for feeling music of a curatorial type and, as such, it might influence how music modulates our emotions. Before analyzing the type of influence that AI might exert over musical affectivity (Sect. 5), I will explain how AI as a tool for feeling music works. It will be argued that AI curates musical affectivity by operating a shift from musical affective affordances to features. AI processes musical affective affordances *as represented in* numerical features to curate affective-based musical playlists.

4.1 AI and Music Curation

It has become common knowledge that we are living in an "age of musical plenty", to quote the subtitle of a book by music critic Ratliff (2016). The digitalization of enormous catalogues of music and the popularization of streaming platforms integrated into portable devices have radically increased the availability of music. This new situation in which listeners find themselves is often described by data scientists working with music recommender systems as a scenario of *information overload* (cf. Seaver 2015; p. 38). The overabundance of music available is supposed to be detrimental for listeners: it makes finding music harder; it makes choosing what to listen to even more challenging. In sum, "musical plenty" risks disorienting listeners. One could question those assumptions, but what matters here is that, as shown by anthropologist Seaver (2015), those beliefs are widespread among researchers and stakeholders developing computational tools to solve what they assume is a problem for music listeners. And the solution proposed takes the form of music recommender systems, i.e., computational tools that employ cutting-edge AI algorithms (and data sciences techniques more broadly) to "provide guidance to users navigating large collections" of music (Schedl et al. 2022, p. 453).

Indeed, scholars have noted that, at some point, music streaming platforms went through what has been called a curatorial turn (Bonini and Gandini 2019). Streaming services started to abandon the label of "neutral intermediaries" or mere "distributors" and shifted their strategy more and more towards music recommendation (cf. Eriksson et al. 2019; p. 72). At this point, services that offered algorithmic analysis of musical data – such as The Echo Nest, acquired by Spotify, and Music Genome Project, acquired by Pandora – gained prominence in the industry. This was anticipated by Brian Whitman, a pioneer in the field of music recommendation and co-founder of The Echo Nest. In his PhD thesis from 2005, he stated the following:

> "[…] we're faced with a glut of data that gets worse every day and careening standards and copyright miasmas, and yet we still search for our music by filename, simple metadata such as artist or album title, or through sales-based recommendation systems. Computers are better at making sense of large amounts of data: they have more patience and don't give up so easily. The goal of our work is to make machines link music to semantic features or the outside world for the purposes of organization, recommendation, or classification. If we do it right, they'll have the same knowledge about the music as the aggregate of your entire community: they can tell you about similar sounding music, or recommend new artists no one has heard yet, or make playlists for you." (Whitman 2005; p. 17).

Since then, the role of AI in music recommendation has not ceased to increase, reaching higher levels of autonomy and sophistication. This has led many scholars and critics to question whether algorithmic curation might end up diminishing musical diversity, hardening people's taste, promoting passive and distracted musical experiences, perpetuating biases, among other consequences (Born et al. 2021; Hesmondhalgh et al. 2023).

Be it as it may, we know that AI is being employed to (partially) automate the task of music curation. And we know that, because of its use in curating music, AI might be influencing various aspects of musical cultures. Though little attention has been paid to the relationship between AI and musical affectivity in that context, *it is my hypothesis that musical affectivity is one of the aspects of musical cultures that might be impacted by the intervention of AI in music curation.*

4.2 AI Curates Musical Affectivity

In fact, one of the most popular applications of algorithmic music curation is in the design of affective-based playlists.

In Spotify, for example, one can find several examples of such playlists curated by the platform. Moreover, it seems that researchers and stakeholders have high expectations regarding the use of AI to enhance musical affectivity in the near future (Whitman 2005; Greenberg and Rentfrow 2017; McGroarty 2020; Haruvi et al. 2022; Arielli 2024). To be fair, Spotify does claim to have a team of human editors, so we cannot say that those playlists are 100% curated by AI systems. However, even assuming the participation of human editors, their decisions are so entangled with the algorithmic analyses that it makes sense to define those affective-based playlists as the result of an "algo-torial logic", a mix between algorithmic and human curatorial processes (cf. Bonini and Gandini 2019). Bonini and Gandini (2019; p. 4) define the "algo-torial logic" as an "intermingling between algorithmic affordances and human agency in music curation". Be it as it may, assuming that AI is playing a significant (and ever more autonomous) role in the curation of affective-based playlists, and admitting the importance of music as a tool for feeling, *it is urgent to ask to which extent AI might impact musical affectivity*.

My hypothesis is that, given their (actual and expected) role in the design of affective-based playlists, there is no doubt that AI is a tool for feeling music of the curatorial type. As such, we can say that AI might influence how music modulates our emotions. AI as mediator in affective-based playlists is not neutral in relation to music's capacity to situate our affectivity – just like a human curator, their understanding and choices of musical affective affordances, might influence music's affective power, as was previously argued in this paper (Sect. 3). Therefore, if we want to determine the extent to which and in which ways the curatorial practices of/with AI might be influencing musical affectivity, we need to first clarify *how* AI operates such curatorial practices. How does AI "understand" and "choose" music to curate affective-based experiences to listeners? And could its "understanding" and "choices" be capable of enhancing, lessening, or transforming in some way or another music's affective power?

In general terms, music recommender systems collect and process not only data related to users (e.g., profile, behavior, context, queries), but also data coming from the songs, including aspects of the *audio content* of the songs. Though it is possible to build a recommender system that analyses only user-item interactions (e.g., collaborative filtering technique), the analysis of audio data seems to be particularly relevant in the task of affective-based recommendations. For example, the analysis of audio content can be crucial to filter which songs could be more relaxing and which ones could be more upbeat among millions of possible choices available in a catalog[8].

In Music Information Retrieval (MIR) research, audio data of songs is analyzed in terms of *features*. In general terms, features are numerical representations of *aspects* of the audio data analyzed. In MIR, features might be low-level (e.g., loudness, timbre) or high-level features that get closer to how humans perceive aspects of the music (e.g., key, melody). There is a subfield of MIR called Music Emotion Recognition (MER) dedicated exclusively to the identification of features that are particularly indicative of the affective dimension of the song analyzed. We know that Spotify's system, for example, can extract and process at least 12 types of high-level features: acousticness; danceability; energy; instrumentalness; key; liveness; loudness; mode; speechiness; tempo; time signature; valence (Panda et al. 2021). In Pandora's system, up to 450 features can be extracted per song, including features such as "prominent backup vocals", "abstract lyrics" and so on (Schedl et al. 2018; p. 98). Though we do not have more information about how exactly those services use those features in the design of affective-based playlists, it seems very likely that they at least participate in the curatorial process of those playlists.

But, regardless of the specific function that those features might have in any music recommender system in particular, *what is important to understand is that many researchers and stakeholders believe that now that we can extract and process multiple features from songs' audio data and compare them with consumption behavior on multiple levels (e.g., context, physiology, habits) using AI algorithms, we should be able to learn, model, automate, and possibly enhance more and more the affective power of music* (Whitman 2005; Greenberg and Rentfrow 2017; Schedl et al. 2018; McGroarty 2020; Haruvi et al. 2022; Arielli 2024). As experts on Music Emotion Recognition say, "features are arguably the key factor to any machine learning problem" (Panda et al. 2021; p. 238) – and the curation of affective-based playlists (not to say the curation of music in general) *is* being treated as a machine learning problem. Hence their conclusion as to what should be done to improve the performance of AI in that task:

> "[…] we believe that novel audio feature extractors, are needed to improve this as well as other MIR problems, since most MIR solutions are generic, 'without relying on musically meaningful features'. These novel features should be higher-level (i.e., closer to

[8] "In order to build emotion-aware MRS, it is therefore necessary to (i) infer the emotional state the listener is in, (ii) infer emotional concepts from the music itself, and (iii) understand how these two interrelate." (Schedl et al. 2018; p. 108).

> human knowledge), providing ways to uncover interpretable rules between emotions and a handful of audio cues […]" (Panda et al. 2021; p. 244).

Based on that, we can infer that the extraction and analysis of audio features by AI algorithms (and related data science techniques) are key variables in *how* AI curates or might curate affective-based playlists. We cannot say yet that affective-based playlists are being curated exclusively by AI systems informed by such features. However, we can certainly assume that the knowledge generated by such AI systems already plays some role – and is likely to play even more central roles – in that kind of music curation, be it by autonomously generating *some* of the affective-based playlists, or in the form of "algorithmic affordances" (cf. Bonini and Gandini 2019) that inform the decision of human curators or editors curating those playlists.

4.3 From Musical Affective Affordances to Audio Features (and Back)

The shift from affordances and features seems to be characteristic of how AI is being used to curate affective-based playlists[9]. Therefore, it is important to analyze this relationship further. This analysis will be useful to clarify what kind of impact AI may have on musical affectivity (Sect. 5).

I believe that the extraction of features from audio data, and more specifically, features that are (supposedly) indicative of the affective power of the songs, can be defined as *tentative* numerical representations of musical affective affordances. Features are an attempt to operationalize musical affective affordances by translating them into numerical representations that can be extracted and processed by algorithms. The assumption that features represent more or less accurately musical affective affordances is fundamental to justify the use of AI to curate affective-based playlists. Thus, we could speak of a tentative substitution of the human-based experience of musical affective affordances by the AI-based numerical representation of those affordances. Many researchers obviously expect that the AI representation could substitute without any significant loss the experience of the affective affordances, or that the AI representation could even do a much better job in capturing musical affective affordances (e.g., Greenberg and Rentfrow 2017; McGroarty 2020; Haruvi et al. 2022).

It is interesting to note that when Krueger defines musical affordances, he refers to a "relation between a feature of the environment (e.g., particular structural qualities of a piece of music) […] and a perceiver-side ability or skill (e.g., motor capacity, perceptual, and affective sensitivity) enabling the pickup and appropriation of this structural feature, on the other." (Kruger 2011, p. 5). However, while Krueger refers to features as elements perceived from the perspective of human experience, nowadays, in machine learning research that power AI-based curatorial practices, features are numerical representations without the phenomenological dimension that characterizes human perception.

Philosopher Gramelsberger (2020) has demonstrated that this shift from the "phenomenological orientation of media towards the human" (Gramelsberger 2020; p. 32) to algorithmic sensor technologies is typical of our current stage of technological development. In this sense, the shift operated by AI from musical affective affordances to features seems to be part of this wider cultural and technological transformation described by Gramelsberger (2020). Moreover, another relevant trait of this shift of media from humans to data is that algorithmic representations not only substitute the phenomenological perspective: algorithmic representations also return to human-level experiences via generated and curated images, texts, sounds, products, and so on. This is what Gramelsberger (2020) calls the "mapping back" effect. First, media and information experienced by humans on the phenomenological level are mapped by algorithmic technologies that operate beyond/under the threshold of human experience. Then, they curate and design "human-centered" media and information, thus mapping back their algorithmic representations onto humans.

According to Gramelsberger (2020), affective computing is a paradigmatic example that illustrates the application and the consequences of that epistemic shift from affordances to features. She analyzes the example of emotion recognition in facial expressions, but we could certainly apply her conclusions to the case of musical affectivity: "[o]f course, affective computers can only recognize what we feel if we express our feelings correctly — that is in terms of a machinic understanding of emotion expression" (Gramelsberger 2020; p. 46).

Indeed, as one can suspect, this back-and-forth movement between affordances and features can be extremely problematic if we acknowledge that the shift from the phenomenological perspective (affordances) to the numerical representations (features) might not be neutral. I will develop that point in Sect. 5. For now, my argument can be summarized as follows: AI is being employed to extract and analyze audio features. In some cases, those features are intended to be numerical representations of musical affective affordances. Affective-based playlists might be

[9] An interesting example of this widespread association is the paper by Duman et al. (2022; p. 1) that starts as follows: "Previous literature has shown that music preferences (and thus preferred musical features) differ depending on the listening context and reasons for listening […]". This presupposes that the analysis of audio features can reveal why users consume this or that type of music, e.g., listening to dance music to uplift one's mood.

(and are probably already being) curated autonomously by AI systems operating with musical affective affordances *as represented in* features or by human curators informed by the "algorithmic affordances" generated by AI (cf. Bonini and Gandini 2019). It is in that sense that I contend that *AI is a new tool for feeling music of curatorial type characterized by a shift from musical affective affordances to audio features that enable the very AI-based curatorial practice.*

Now that we understand *that* AI is being employed in the curation of affective-based playlists and *how* AI as a tool for feeling music operates, we are ready to tackle the following question: What kind of impact might AI exert over musical affectivity? Should we expect a new age of discoveries about and enhanced experiences with musical affectivity, as some scholars seem to suggest (e.g., Greenberg and Rentfrow 2017)? Or could this shift from musical affective affordances to features exert a negative impact on musical affectivity?

5 Musical Affectivity in the Age of AI: What Can We Expect?

I have argued that AI is being employed, with growing levels of autonomy, in the curation of affective-based playlists. Hence, just like human curation functions like a tool for feeling music, we can say that AI is functioning as a tool for feeling music of curatorial type. In my analysis, I have shown that AI as a tool for feeling music is characterized by a shift from musical affective affordances as experienced by humans to numerical features that were supposed to represent those affordances to computer systems. It is through the extraction and analysis of features that AI intermediates the curation of affective-based playlists – sometimes autonomously, sometimes by aiding human curators with "algorithmic affordances" (cf. Bonini and Gandini 2019). That being said, I would now like to address the following questions: what can we expect from AI as a tool for feeling music? Are we headed towards the music as an *enhanced* tool for feeling?

Evidently, different types of AI systems might influence musical affectivity differently. As we can infer from what was presented earlier in this paper, researchers in areas such as MER are working to develop novel solutions in terms of feature extraction and analysis. Therefore, depending on the capacity of each system to operate the shift from musical affective affordances to features, their influence over musical affectivity will vary. In other words, we could say that each AI system will have its own 'understanding' of musical affectivity. This 'understanding' will be defined to a great extent by the features it manages to extract and analyze (but also by the correlations it manages to establish between features and consumption behavior). Some systems might be able to handle only very low-level features (e.g., volume, duration) while others, like Spotify's system, might be able to represent high-level features such as valency and danceability. One could speculate that perhaps some AI systems will be able to perfectly emulate humans' capacity to capture musical affective affordances. In other cases, however, the AI system might underperform, outperform, or simply perform differently vis-à-vis human agents. In that sense, the capacity of AI systems to "understand" musical affectivity will determine their ability to curate musical affectivity – transforming, lessening, or enhancing musical affectivity. For example, if their 'understanding' of musical affective affordances is too superficial, the resulting affective-based playlist will underexploit music's capacity to modulate our emotions – like in a setlist curated by a human with little knowledge about and intimacy with music. However, if a certain AI system is capable of managing multiple audio features that are relevant for human listeners, that AI system might be able to uplift one's experience of musical affectivity.

That being said, one can, nonetheless, anticipate some possible scenarios. I will focus on the cases in which the adoption of AI as a tool for feeling music might raise some concern, as it might in impact musical affectivity in negative ways. I am assuming that if AI could become a perfect emulation of how humans capture musical affective affordances and/or if AI could become even better, like an extraordinary musical curator, those cases would not be so concerning, at least not from the perspective of the listeners. For an updated analysis showing in which ways AI could enhance human aesthetic experiences, the reader can check Arielli (2024).

Arielli (2024; p. 10) contends that artificial systems dealing with aesthetics need to take into account "the *limits* and *biases* natural to human perception and cognition". This is because such systems are capable of registering and processing data that goes way beyond the scope of human perception. Therefore, he claims, there needs to be a sort of 'alignment' between how AI 'understands' the aesthetic object and how humans experience aesthetic objects. However, we should also consider *the limits and biases of the AI systems* and how those could impinge on human perceptions and experiences.

A potential negative consequence of adopting AI as a tool for feeling music relates to the *limitations of AI as a method*. As was suggested before, in the shift from musical affective affordances to features that intend to represent them, AI might misrepresent, oversimply, and even ignore many musical affective affordances that humans can grasp. This might result from the fact that AI exceeds human's capacity to process data, as Arielli (2024; p. 10) suggests, but it might also have other causes, such limitations in the training and/or evaluation phases of the model. In fact, one could even speculate that this imbalance between human and AI approaches might be unavoidable once we shift from the phenomenological domain of affordances to the numerical domain of features. Be it a temporary problem or not, we could say that such limitations could result in the AI-curated affective experience being perceived by listeners as inefficient, boring, unsurprising, uninteresting, meaningless, and so on.

Another negative scenario would involve the use of AI to efficiently operationalize and exploit certain aspects of musical affectivity, such as clichés, habits, trends, and, more concerningly, addictive patterns (de Aguiar 2023). That scenario could result from *biases in AI models*. In this case, the shift from musical affective affordances to features is not limited or superficial; it is simply optimized for a biased goal. It involves using AI to represent certain aspects of musical affective affordances that could be useful for commercial purposes, even if they are problematic in relation to aesthetic and ethical goals[10].

In both cases, the limitations and/or biases of the AI employed might be 'mapped back' onto users through the products they generate, e.g., by installing new habits. The mid- to long-term exposure to affective-based playlists curated by limited and/or biased AI could eventually change the very sensibility of listeners to musical affectivity. In an early commentary on AI-based music curation, music critic Sasha Frere-Jones speculated that "the anonymous programmers who write the algorithms that control the series of songs in these streaming services may end up having a huge effect on the way that people think of musical narrative—what follows what, and who sounds best with whom." (Frere-Jones 2010; p. n/a). I believe the same applies to musical affectivity. The limitations and/or biases of AI curating musical affectivity might contribute significantly to install new sensibilities in the listeners – sensibilities that are adapted to the limitations and/or biases of the AI.

The potential consequences aforementioned are inferred from the fact that the use of AI to curate affective-based playlists is characterized by a shift from musical affective affordances to features. Since each system will operate that shift in a different way, each system will articulate the limitations and/or biases in a different way. Thus, empirical studies are needed to investigate potential limitations and/or biases in specific systems and to what extent those limitations and/or biases are being 'mapped back' onto the users of those systems. Preliminary evidence seems to indicate that limitations and biases, such as the ones referred before, can already be found in AI systems currently employed to curate affective-based playlists (Schedl et al. 2018; Panda et al. 2021). Sociological literature on the experience of listeners consuming music through music streaming platforms could also be read as indicative of a potential case of 'mapping back' (Pedersen 2020) – though obviously, the impact of the streaming platforms on listeners cannot be reduced to the algorithmic infrastructure only. Be it as it may, even if we ignore the preliminary evidence and treat them as merely *potential* consequences that refer to subtle changes that *could* happen in the mid- to long-term, I believe that conceptualizing them is of utmost importance to identify them if and when they happen as well as to design strategies to prevent them from happening.

6 Conclusions

In this paper, building on the framework of situated affectivity and on the notion of musical affective affordances, I have argued that the experience of music as a tool for feeling might be altered, enhanced or lessened depending on the tools for feeling music. I investigated the extent to which AI might be considered a case of tool for feeling music and examined the influence it could exert over musical affectivity. To conduct this analysis, I first established that curation functions as a tool for feeling music and demonstrated that AI is not only employed in curating music but also in curating affective-based musical playlists more specifically. After examining *how* AI is used in these cases, I concluded that, in curating affective-based musical playlists, AI operates a shift from musical affective affordances to numerical representations of them, i.e., features. Based on this conclusion, I argued that AI might negatively impact musical affectivity due to methodological limitations and/or biases inherent in the shift from affordances to features. This impact could manifest, for example, in the form of simplifications or misrepresentations of musical affective affordances. Limited and/or biased representations of musical affective affordances might ultimately influence listeners' perceptions and experiences, leading them to become adapted to the content curated by AI.

I hope to have demonstrated that the introduction of AI as a mediator in music curation has implications not only at the economic level or in terms of musical diversity. Musical affectivity – or music as a tool for feeling, more specifically – is also impacted by AI. Although, currently, the consequences of AI for musical affectivity may not be as evident and widespread as in other domains of musical cultures,

[10] See, for instance, the following examples of research papers presenting AI systems developed by companies such as YouTube (Covington et al. 2016), Spotify (Anderson et al. 2020), and Disney (Deng et al. 2017). In those and related cases, the focus on commercial performance and optimization might be interpreted as examples of biased goals that could eventually even go against aesthetic and ethical values.

music remains a highly popular tool for feeling. Therefore, it is crucial to monitor and understand these changes.

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