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Algorithmic Arias: Navigating the Melodic Maze of Music and Mind

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ABSTRACT

Music has a profound impact on our emotional well-being, and music therapy has proven effective in various healthcare settings. However, traditional methods of music therapy lack real-time personalization. This research explores the potential of personalized music therapy using Affective Algorithmic Composition (AAC) and facial recognition technology. The focus is on harnessing the power of AAC to generate music tailored to an individual's emotional state in real-time. Existing research confirms the strong connection between music and the brain, demonstrating the effectiveness of music therapy in various healthcare settings, and facial recognition technology provides a cost-effective and versatile tool to measure these emotions. While the field of AAC is experiencing significant growth, user preferences and the factors influencing them are crucial for developing successful real-time personalized music experiences. To gain insights into these aspects, a survey (n=160) was conducted to collect data on demographics, music listening habits, and influences on musical preferences across a range of ages. While the sample had a significant portion of teenagers (14-15 years old), responses from all age groups contributed to a comprehensive understanding of music preferences and their potential connection to emotions across the lifespan. Future studies will focus on refining emotion detection algorithms, optimizing AAC for real-time music generation, and conducting clinical trials to evaluate the effectiveness of this approach.

Review of Literature

Introduction

The human brain is known to resonate with the rhythm and melodic whispers of music. From the ancestral drumbeat to the soaring symphony, music has been in use for thousands of years and weaves a tapestry of emotion that can transcend language and culture. We delve into this intricate relationship between music and the mind, culminating in the proposal of a novel prototype. By using computer vision in conjunction with the knowledge of specific musical components, algorithms can be created to make highly effective and personalized music, serving especially useful in contexts where cost-effective solutions to entice human brains into particular mental states are necessary. The aim of this paper is to examine automated music generation using Affective Algorithmic Composition (AAC) tailored to an individual, discuss the motive and reasoning behind Facial-Expression Recognition algorithms [FER] as tools to gather the required data, and assess the necessity and opportunities of this technology, including greatly enhancing mental health therapy and patient care.

Background

The impact of music on human emotion remains an enduring phenomenon. Dating back to the Paleolithic era, over 40,000 years ago, the inclination of humans towards musical instruments suggests its potential status as a survival tool

(Zatorre, 2018). In the sixth century, Pythagoras prescribed music mixed with a particular diet to patients who came to him for good health (White, 2001). Recognizing the therapeutic impact music had on her patients during the Crimean War, Florence Nightingale found how wind instruments with sustained tones positively impacted their conditions while discontinuous tones had the opposite effect (Nightingale, 1946; Nilsson, 2008). With the advent of the study of music theory and even more recent developments in sensory perception, research has found direct links between particular musical components and induced states of mind, such as loudness (Reybrouck et al., 2019), timbre (Quinto et al., 2013), tempo (Liu et al., 2018), and especially the major-minor dichotomy (Bharucha & Stoeckig, 1986; Carraturo et al., 2023). These characteristics are manipulated to not only create compelling auditory experiences but also to harness the therapeutic power of music in diverse healthcare applications, ranging from pain alleviation in medical procedures (Nilsson, 2008) to aiding cognitive function in dementia patients (Särkämö et al., 2013; Edwards et al., 2023). Such musical therapy is becoming an increasingly popular non-invasive intervention especially in surgery and the ICU (Lorek et al., 2023). There is a shared embodiment of music-induced emotions even in geographically distant cultures – particular acoustic and structural features of music are consistently associated with self-reported music-induced bodily sensations across people from North America, Europe and China when listening to Western and East Asian music (Putkinen et al., 2024). Music works over language and cultural barriers.

In parallel, algorithmic composition is a growing field that offers a promising route for creating novel and engaging musical experiences tailored specifically to the brain (He, 2022). *Affective* algorithmic composition (AAC) exploits computer aid in order to generate new music with particular emotional qualities and affective intentions (Williams et al., 2017). Instead of relying on past listening history, which do not fully capture a person's evolving tastes or immediate emotional responses, using real-time metrics can lead to a more adaptable approach to gauging musical taste. Concerning musical taste being utilized in medical interventions, there is sizeable importance placed on the patient preferences in such endeavors – research suggests that "it is the act of making a choice that determines the greatest effectiveness of the [musical] procedure" (Guerrier et al., 2021). Music has more pronounced effects on listeners the more it is tailored to them, and the precision of algorithms can make this neurological effect even stronger (Huang & Lin, 2013; Woods et al., 2019).

Affective Algorithmic Composition

The first instances of computer use for music composition emerged around the mid-1950s, when computers were still very expensive and slow. Created through rule systems and Markov chains, Hiller and Isaacson's *Illiac Suite* was a string quartet entirely composed by the ILLIAC I computer at University of Illinois at Urbana–Champaign by the two professors in 1957, and is commonly cited as the first electronically generated score (Hiller & Isaacson, 1958; Fernández & Vico, 2013).

It is known that particular musical features elicit certain responses in people. The way music affects the brain has substantial impact that only gets better with algorithmic precision, and programs which are designed with this goal in mind are part of Affective Algorithmic Composition. Neuroscientific studies demonstrate this impact, revealing heightened emotional responses with algorithmically precise classical compositions (Agres et al., 2023). Beyond classical, services like Brain.fm utilize algorithms that tailor music's acoustic features to sustain attention in people with varying attentional difficulties in a variety of genres (Woods et al., 2021). Electronic composition systems already show some level of human affectance – one such system to control emotional expression in computer-aided music generation improves composition and performance ability by musicians and non-musicians alike (Grimaud & Eerola, 2020), while more systems like "MoMusic" (Bian et al., 2023) and the "affective remixer" (Chung & Vercoe, 2006) serve as working models. An artificial system capable of influencing peoples' affective states through AI-generated music was developed through the use of "biofeedback loops" for gauging affect and updating acoustics in real-time (Williams et al., 2020). Such "intelligent musical interfaces" measure cognitive states of people *implicitly* in real-time to create appropriately toned music without conscious effort on the part of the user (Yuksel et al., 2019; Hou, 2022). A systematic review on AAC systems highlights their ability to trigger emotions in humans, but designing such systems to stimulate users' emotions remains a steadfast challenge due to the lack of aggregated existing literature (Wiafe. & Fränti, 2023). Algorithmic music composition also frees up time for valuable human resources and enables people without musical expertise to create desirable music (Meier, 2014).

Real-Time Facial Recognition

The proposed system observes facial expressions for input data, as this method is desirable for measuring effect. Facial recognition using computer vision is much more cost-effective, versatile and practical than costly electroencephalogram (EEG) and facial electromyography (fEMG) machines requiring bothersome wiring to measure affect; intrusive methods are phasing out and recent advances are only making computer vision more accessible (Bahreini et al., 2019). In 2020, a proposed convolutional neural network CNN method designed to be as computationally light as possible outperformed most competitors when detecting micro-expressions in the face and could do so in 24 ms, making it very suitable for real-time embedded applications with limited memory and computing resources (Belaiche et al., 2020).

Research also suggests a disparity between self-reported feelings and true measured emotion (Franek et al., 2022), solidifying the cold-hard nature of facial data and its lack of bias. Facial data is also easy to gather from any subject and can circumvent cultural and language barriers that traditional methods fall prey to (Jack et al., 2012; Ekman, 1971).

There exists a strong relationship between music and emotion, and their cumulative effect on the visage is very apparent. Research on audience facial expressions during music performances establishes the link between observed emotions and music experiences, emphasizing the role of facial expressions in gauging affect (Kayser et al., 2021). Another investigation into such expressions during emotionally charged moments and musical experiences suggests a very strong connection between music-induced emotions and specific facial expressions (Klepzig et al., 2022), and repeated exposure to emotionally evocative music is found to induce “liking and smile responses” in people (Witvliet & Vrana, 2007). Additionally, various prototypes of systems using facial expressions to output playlists and recommendations have been proposed in recent years (Mishra et al., 2020; Florence & Uma, 2020; Athalve et al., 2021; Srinivas et al., 2022; Shivam et al., 2023).

Advantages Provided in Medical Use

The necessity and opportunities of this technology include greatly enhancing mental health therapy and patient care. Music interventions, particularly those tailored to individual preferences, are effective and cost-efficient in a medical setting (Galińska, 2015; Golden, 2021). A study found that patient-directed music interventions prove not only more effective in alleviating anxiety among mechanically ventilated ICU patients, but also reduce their hospital stay by approximately 1.4 days saving $2,322 per patient, on average (Chlan et al., 2018).

Studies show promising results from music therapy in substance abuse recovery, particularly on emotional regulation and motivation (Ghetti et al., 2017; Hohmann et al., 2017). Personalized musical therapy administered to 4,968 patients in a meta-analysis found a mean reduction in morphine-equivalent opioid dosage of 4.4 mg compared to the control group, suggesting music as a viable tool to combat opioid dependence (Fu et al., 2020). One study comparing the effects of conventional and algorithmic music in inducing relaxation found that computer-generated music was just as effective as participants’ favorite music in the task (Raglio et al., 2021). In studies analyzing the reduction of felt pain obtained through music, it is consistently found that subjects’ favorite and preferred music outperforms experimenter-selected samples (Timmerman et al, 2023; Valevicius et al., 2023). These findings compose a growing body of evidence supporting musical therapy’s efficacy in improving medical outcomes, and the degree to which music is personalized to specific people is more desirable the higher it is.

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Methods

Methods & Hypothesis

This portion of the study employed a survey research design that falls under both descriptive and correlational research. We hypothesize that there will be significant variations in music preferences and the factors influencing those preferences across different age groups. These variations may be linked to factors like preferred genres and artists, frequency of music listening, musical background and knowledge, etc.

Participants

On 4/26/2024, 160 responses of participants between the ages 12 and 78 were collected. Demographic categories of Age, Gender and Ethnicity were collected.

Materials

The google form is found at https://forms.gle/qfD35bd9KQ6yCDTy9. The questionnaire aims to understand demographics, music listening habits, and influences on musical preferences.

Procedures

The online questionnaire was designed using Google Forms. The questionnaire was crafted to be clear, concise, and unbiased to minimize response bias. The questionnaire link was then distributed through various channels such as email, messaging and social media to reach a broad audience. The charting capabilities of Google Forms were used to extract primary data from survey responses and receive general summaries of results. Google Sheets was used to create graphs, compute statistical measurements like standard deviation and skewness, and create working regression models. Information regarding favorite genres, artists, and mood-influencing kinds of music was collected with the intention of later cross-referencing the genres with the particular timbres they characterize. This can then be linked to certain age groups, people with a particular musical background, etc.

Results

The research question focused on how demographics, music listening habits, and prior musical knowledge influence musical preferences in people. The data analysis on the impact of mood and other factors on listening habits across different age groups directly addresses this through pointed questions.

Figure 1 explores how often participants in the study reported listening to music. The data reveals a clear trend towards frequent music listening, with the majority (73%) indicating they listen to music daily or more than three times a day. Music plays a significant role in the daily lives of a large portion of the surveyed population, which may be attributed to the dominantly teenage composition of the group.

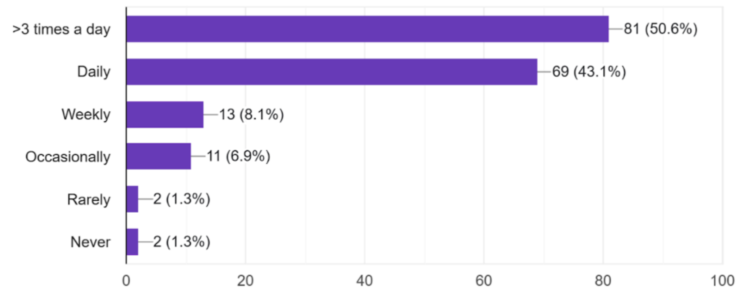

Figure 1. Frequency of music listening in participants.

Regarding the information in Figure 2, here's what can be said about the top 3 reasons why participants listen to music:

Relaxation and unwinding: This was the most popular reason, with 90 (59.6%) participants selecting it.
Improve mood: Closely following in popularity was improving mood, chosen by 91 (60.3%) participants.
Entertainment: 64.2% (97 participants) selected entertainment as a reason for listening to music.
Focus and concentration: While not a top 3 reason, a significant number of participants (65, or 43%) listen to music to help them focus while studying.

Stress and anxiety: Similarly, managing stress or anxiety was a reason for listening to music for 64 participants (42.4%).
Enjoyment of sound: Appreciating the sound of music itself was a reason endorsed by 83 participants (55%).

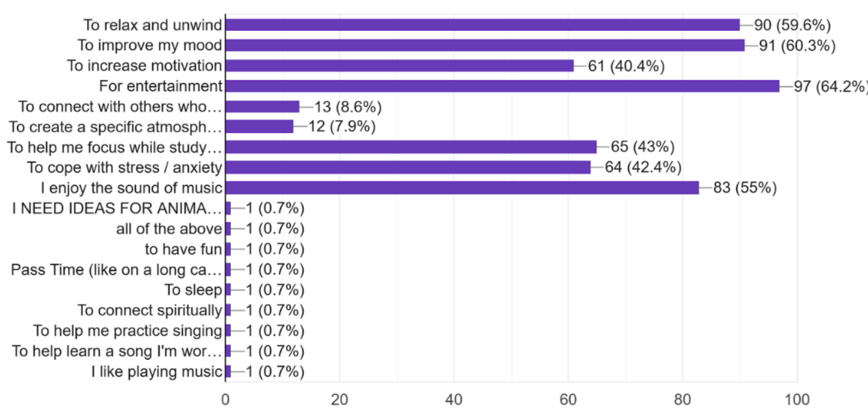

Figure 2. Self-reported reasons for listening to music.

It's also interesting to note that some participants (1%) provided their own reasons for listening to music that weren't among the 9 pre-written options. These included finding ideas for animations, having fun, using music as a pass time (like on long car rides), using it to sleep, for spiritual connection, and to help with singing practice. Figure 2 affirms that people listen to music for a variety of reasons, with relaxation, mood improvement, and entertainment being the most popular choices in this study. There is a wide variety in the reasons that participants give as their primary purpose in listening to music. The exaggerated proportion of younger teens in the sample manifested in the distribution of the responses.

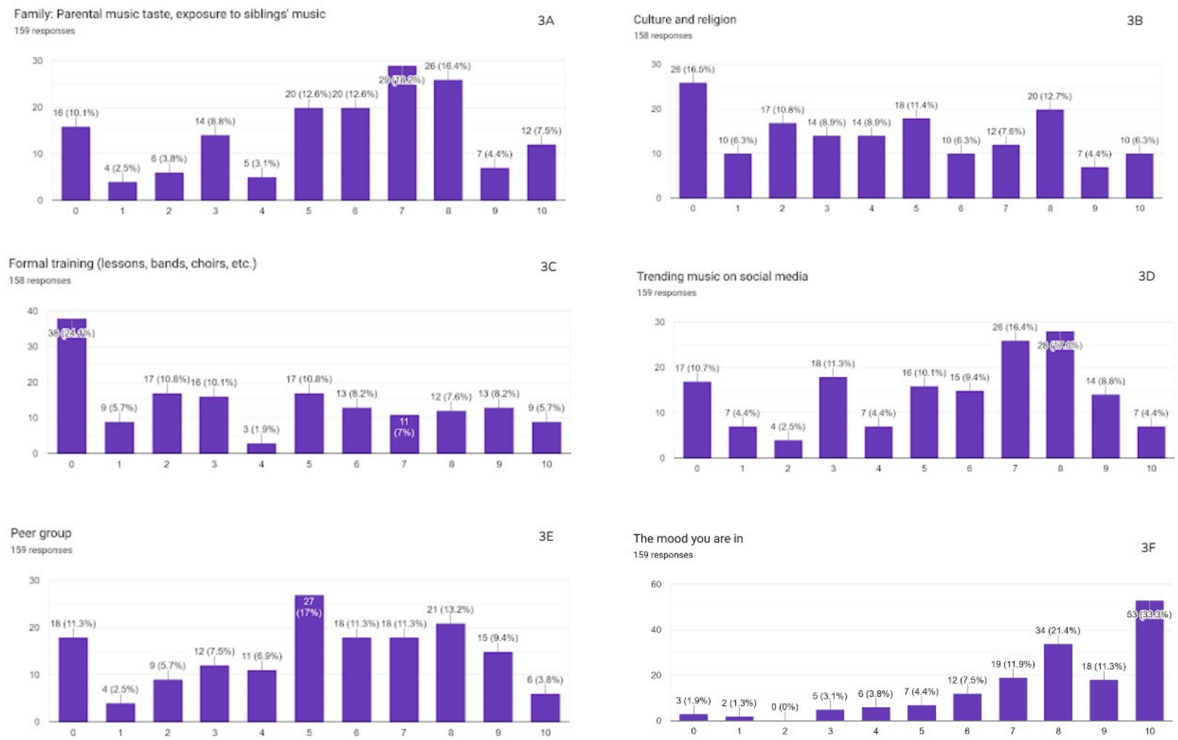

Figure 3. Family influences on current music preferences (3A), Culture & religion influences preferences (3B), Formal musical training influences (3C), Trending music influences (3D), Peer group influences (3E), Mood influences (3F).

Analysis of this data reveals some interesting trends about how musical preferences and influences may change throughout life. The impact of mood on musical preference is massively skewed left (skewness = -1.323184917) indicating an apparent tendency to choose music that highly reflects one's current mood, which also follows from common sense. Moderately skewed left are the effects of current trending music (skewness = -0.5012948051) and that of family (skewness = -0.5560428157).

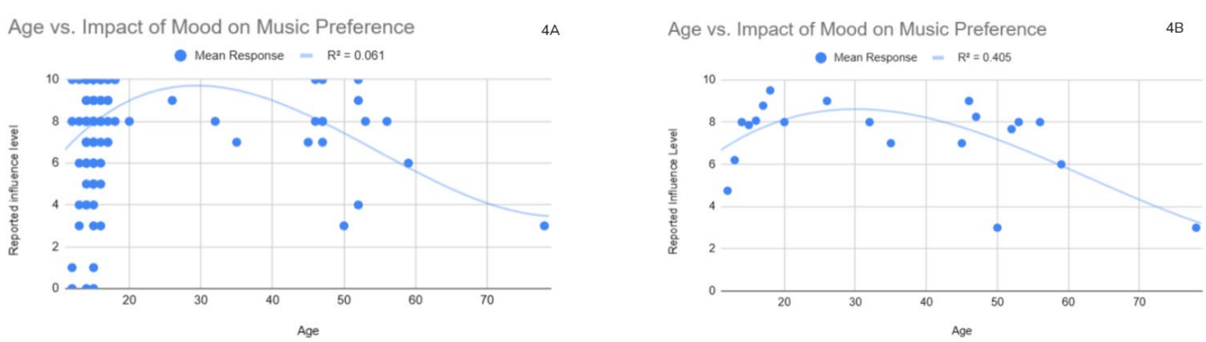

Figure 4. Trendlines for mood influences on current music preferences: having individual responses as observed values (4A), having the mean response of each age group as observed values (4B).

When age is compared to these impacts, a pattern arises showing a somewhat parabolic curve for emotional impact, suggesting that there may be an age or period of life where mood has a greater influence on the musical habits of the average person. However, a cubic regression yields the R^2 value to be only about 0.068, which limits our ability to definitively establish a correlation between age and the emotional impact of music – though the curve does hint at a potential period in life where mood might play a stronger role in music selection. Upon further adjusting via averaging the y-value for each age, the R^2 value rises to 0.402, still indicating a low correlation, exacerbated by the high variance in this data.

Discussion

These findings warrant further investigation and data collection (i.e. sheer number of responses from more diverse age groups) to facilitate pattern-seeking and to understand the nuances of how these factors shape music preferences. The skewed age distribution in the responses limits the generalizability of the findings. The online format might not have reached as many older adults who are less likely to use online surveys. This questionnaire focused on self-reported data, which can be subjective and prone to bias. Despite the limitations, analysis reveals interesting trends about how musical preferences and influences change throughout life. Comparing and contrasting responses from teenagers to those from adults may show significant differences in how music influences emotions. The large number of responses from teenagers allows for a more in-depth analysis of their specific music interests and emotional connections to music.

Conclusion

This paper has explored the potential marriage of music and technology through Affective Algorithmic Composition (AAC) and facial recognition. By harnessing the science of musical impact and the efficiency of algorithms, such a system has certain purpose beyond sole entertainment in crucial sectors like mental health therapy, pain management, and substance abuse recovery. This personalized approach holds significant advantages over generic interventions and transcends cultural boundaries, as the literature suggests, and while challenges remain in refining AI-based emotion recognition and tailoring music in real-time with the most efficient/high-yield algorithms, the potential to create a strong "biofeedback symphony" is immense. Further research and development in this field could unlock a new era of music therapy, where personalized melodies become powerful allies in promoting health for people worldwide.

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