

Harmony and Personality: Analyzing Connections Between AI-Generated Music Preference and Personal Traits

Michael Noh & Caitlyn Kim

Received June 24, 2024

Accepted December 26, 2024

Electronic access December 31, 2024

Artificial intelligence (AI) has made progress over the last decades to the extent of being able to generate creative works, one field of which is music. Prior research has indicated that humans tend to show negative bias against AI art, though there have been contrasting results on whether humans can accurately distinguish AI artists from human artists. Previous studies suggest that persons with different characteristics within the Big 5 personality traits, age demographics, creative identity, and familiarity to AI technology perceive AI visual artworks differently. However, no studies have investigated this phenomenon in the realm of AI-generated music. Therefore, this study aims to examine the relationship between individual characteristics and perception of AI within the field of musical composition. We hypothesize that younger people will be able to distinguish between AI- and human-generated music better than older generations. Furthermore, we hypothesize that people who score high on openness and agreeableness will exhibit less negative attitudes towards AI-generated music, while people who score high on neuroticism and conscientiousness will exhibit more negative attitudes towards AI-generated music. In a sample of 31 participants who responded to the online survey, we found significant correlations between perceived composer's identity and participants' preferences, while we did not find any significant correlations between personal characteristics with participants' accuracy and preferences. Implications on our understanding of AI generated artwork are discussed.

Introduction

Music has historically played a significant role in humanity. The importance of human experience in music making and performance has been steadily supported by research suggesting that music stimulates social instincts and interpersonal interactions by invoking collective experiences—functioning as a link between one's social identity and the rest of society^{1,2}. Studies on neuroscience also show that the human brain activates its neural networks on social emotions and language when exposed to music, adding support to the view that music is a means of connection³. Moreover, cognitive strategies unique to humans such as imagination, problem-solving, and metacognitive techniques are utilized in the process of musical composition⁴. These studies demonstrate the importance of humans as agents in musical production, as well as how music's significance extends beyond its artistic value into the domains of social bonding and cognitive stimulation. In the last decades, artificial intelligence (AI) has been recognized as another possible artistic agent. Due to the wide-ranging capabilities of artificial intelligence, including the ability to combine familiar ideas, analyze commonalities between concepts, and develop originality based on contexts, AI has shown to mimic and enhance human creativity⁵. In the contemporaries, AI has made significant emergence in forms that include literary art, visual art, and auditory art⁶. With this, the current paradigm explores the synergy between

human creativity and AI-powered autonomy rather than focusing on the replacement of creative fields, looking at areas such as “information extraction”, “analysis”, and “enhancement”⁷. Specifically, generative AI in music are autonomous systems that synthesize previous musical corpus and make compositional decisions to create new musical compositions with variations, melodies, and harmonies without direct human input. These systems are based on machine learning and neural networks, which analyze vast amounts of data on patterns, structures, and styles. For instance, OpenAI's MuseNet predicts the next upcoming note based on probabilistic analysis of the training dataset on a specific musical style⁸; similarly, Music Transformer by Google anticipates the next sequence to come based on likelihood and synthesizes various musical excerpts⁹. Therefore, music generation AI are defined by autonomous systems that differ from traditional approaches in that they generate new music compositions based on machine learning or neural networks that study statistical patterns from past human compositions, rather than from direct human experience and creative identity. This recent trend that explores the connection between humans and AI with creativity stimulated researchers to investigate how we distinguish and perceive AI-generated works. Current literature states that human-made visual artworks are viewed as more attractive and generally preferred over artworks perceived to be AI-generated¹⁰. It also states that humans are biased to correlate what they think of to be intentional and meaningful

images with human-made qualities¹¹. Past research also suggests recognizing anthropomorphic characteristics from an AI, for instance from watching its creative process, people’s prejudices can be overridden¹². On the domain of distinguishability, recent studies suggest people are unable to accurately identify the authorship of AI-generated artworks^{13,14}. Furthermore, these abilities are affected by our personal traits – for instance, higher levels of empathy correlate with improved ability to distinguish AI-generated artworks, whereas higher levels of conscientiousness correlate with the opposite. Personal characteristics also affect preferences, such that higher aged groups show a negative prejudice against AI-generated artworks¹⁴. This study aims to focus on auditory art, more specifically music. Currently, humans’ perceptions towards AI’s ability to generate musical pieces are characterized to be lacking emotional qualities, lower quality, and unsatisfactory compared to those of human counterparts^{15,16}. However, some research shows contrasting conclusions, as a study done on professional musicians reveals that though AI-generated music is thought of to be low quality, knowing the composer’s identity does not produce meaningful differences in the perception of music pieces¹⁷. Lack of meaningful differences were also previously replicated with visual arts as well¹⁸. These qualities are also affected by factors such as the genre of the music, where classical has been shown to be easier to distinguish than electronic¹⁹. Overall, AI-generated music is generally stigmatized against; though there is limited understanding on the possible explanations behind this phenomenon, such as how different individual characteristics affect how one perceives and distinguishes AI music. Therefore, this study aims to add a unique perspective to the current literature on the relationship between humans and AI-generated music by further investigating how personal characteristics, such as age and personalities, are linked to the preference for AI-generated music and the ability to distinguish it from human compositions. Studies in this area are crucial in that they can enhance our knowledge on the perception of AI-generated music, which can in turn encourage future AI systems to be better aligned with human preferences and improve the adaptability and accessibility of AI systems in people’s daily lives. In this vein, this study can build the foundation to advance the integration of AI in musical education, composition, and therapeutic contexts in which generative tools can play a pivotal role in personalization and efficiency. Lastly, exploring this domain also contributes to ethical and philosophical discussions on AI’s authenticity and its role as a creative agent in society. Therefore, three primary aims were examined in this study: (1) replicate previous findings on human bias against AI-generated music and examine the causes behind them (2) identify how demographic variables and characteristics influence the ability to distinguish AI-generated music, and (3) identify which of the big-five personality traits influence responses to AI-generated music. Specifically, the following three hypotheses were examined with the usage of surveys to

measure participants’ preferences, subjective viewpoints and the ability to distinguish AI-generated music.

- H1: Younger people will be able to distinguish between AI-generated music and human generated music better than older generations.
- H2: People who score high on openness and agreeableness will not have a negative bias against AI-generated music compared to human generated music and show high accuracy.
- H3: People who score high on neuroticism and conscientiousness will have a negative bias against AI-generated music compared to human generated music and show low accuracy.

Results

Aim 1: Human Bias Against AI-generated Music

To find the relationship between the actual and perceived authorship of music with preferences, we used paired t-tests. The first model compared the ratings given to music excerpts believed to be generated by an AI and the ratings given to music excerpts believed to be generated by a human. Preferences were significantly higher for excerpts perceived as human-composed than for those perceived as AI-generated, with a mean difference of 1.24 ($t = 6.45, p < .001$; Figure 1), thereby supporting the hypothesis that perceived authorship influences preferences of listeners.

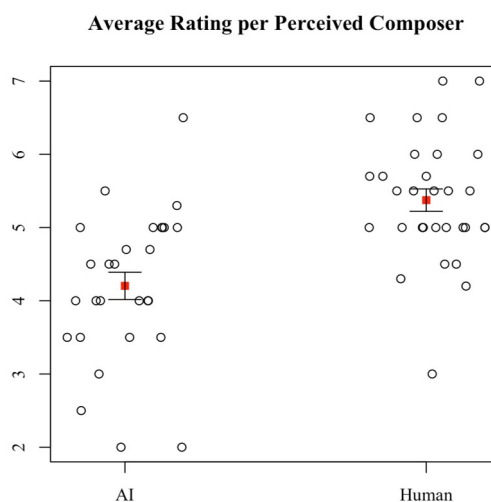


Fig. 1 Average Ratings of AI and Human Generated Music: Perceived Composer

The second model compared the ratings given to music excerpts actually generated by AI and the ratings given to music excerpts actually composed by a human. Preferences were also higher for excerpts actually human-composed than AI-generated

with a mean difference of 0.71 ($t = 3.52, p = .001$; Figure 2), suggesting that the actual composer's identity may affect preferences of listeners too, but on a smaller scale. Effect size calculations showed a large effect for perceived authorship (Cohen's $D = 1.24$) and a medium effect for actual authorship (Cohen's $D = 0.74$). These findings support the hypothesis that perceived authorship influences listeners' preferences, while actual authorship has a moderate effect.

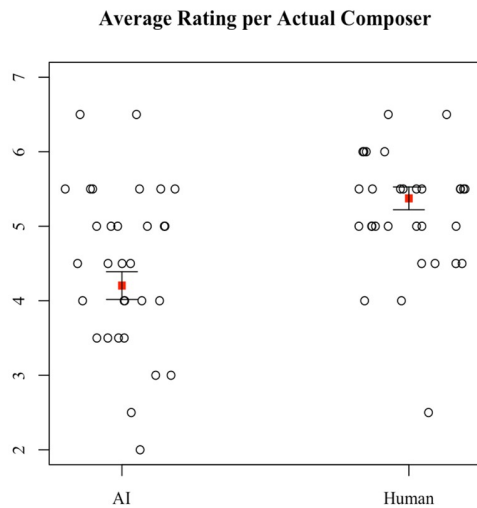


Fig. 2 Average Ratings of AI and Human Generated Music: Actual Composer

Aim 2: Demographic Characteristics & the Ability to Distinguish AI-generated Music

Overall, the average accuracy for participants was 57.3%. This demonstrates that people were generally unsure of the actual authorship of the music but were somewhat able to tell the difference, which ensures that their ratings were actually based on their perception. The average of all ratings for excerpts perceived to be composed by humans was 5.37 out of the 7-point likert scale that was provided. The average rating for excerpts perceived to be composed by AI ($M = 3.80$) was lower than the average rating for excerpts perceived to be composed by humans ($M = 5.37$).

All relations between exposure to music and familiarity with technology were analyzed through linear regression models. Familiarity with technology and music exposure were analyzed in relation to accuracy and ratings for excerpts believed to be generated by an AI (preference for AI music). Contrary to our hypotheses, familiarity with technology had no significant correlation with accuracy ($F(1, 28) = 1.53, p = 0.23, R^2 = 0.018$) or preference for human music ($F(1, 26) = 0.12, p = 0.74, R^2 = -0.034$). Furthermore, exposure to music did not show any significant correlation with accuracy ($F(1, 28) = 1.53, p = 0.23,$

$R^2 = 0.018$) nor with preference for human music ($F(1, 25) = 0.45, p = 0.51, R^2 = -0.022$). Lastly, age also had no significant correlation with accuracy ($F(1, 27) = 0.34, p = 0.56, R^2 = -0.024$; Figure 3) nor with preference for human music ($F(1, 25) = 0.03, p = 0.87, R^2 = -0.039$; Figure 4). Contrary to our hypotheses, linear regression analyses revealed no significant correlations between familiarity with technology, music exposure, or age and participants' accuracy or preferences, suggesting that these factors did not influence their ability to identify or favor human versus AI-composed music in this study.

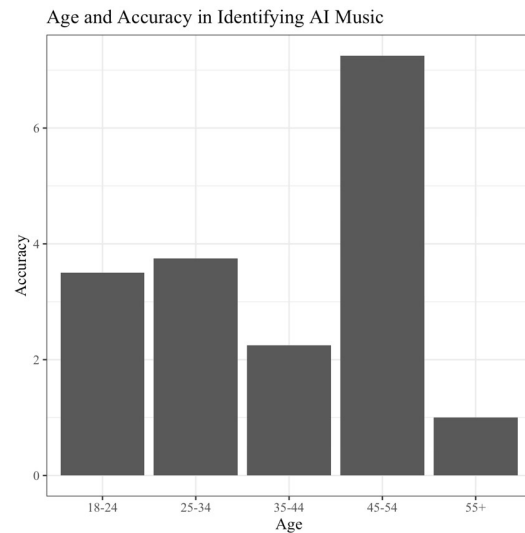


Fig. 3 Age and Accuracy

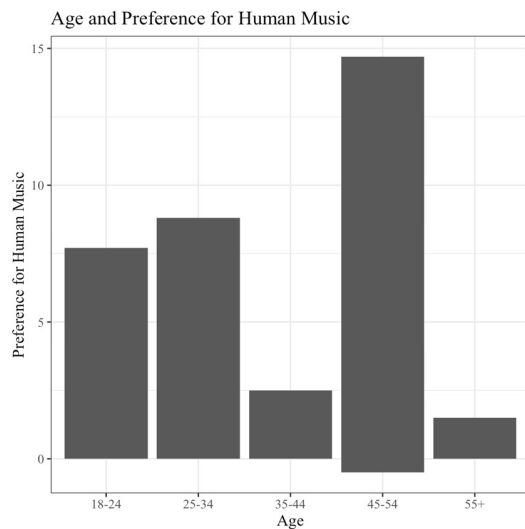


Fig. 4 Age and Preference

Aim 3: Personality Traits and Responses to AI-generated Music

All relations between personality traits, accuracy and preferences were analyzed with linear regression models. The sum of ratings for music believed to be composed by humans was subtracted from the sum of ratings for music believed to be generated by AI to calculate the preference of each participant. A higher preference value indicates a larger preference for music believed to be composed by humans.

Contrary to our hypotheses, linear regression analyses indicated that extraversion was not significantly correlated with either preferences ($F(1, 26) = 0.90, p = 0.352, R^2 = 0.18$) or accuracy ($F(1, 29) = 1.82, p = 0.19, R^2 = 0.027$). Similarly, neuroticism had no significant correlation with preferences ($F(1, 26) = 0.28, p = 0.6, R^2 = -0.028$) or accuracy ($F(1, 29) = 1.4, p = 0.25, R^2 = 0.013$). Agreeableness was also unrelated to both preferences ($F(1, 26) = 2.5e-4, p = 0.99, R^2 = -0.038$) and accuracy ($F(1, 29) = 0.16, p = 0.69, R^2 = -0.029$). Likewise, conscientiousness was not significantly correlated with preferences ($F(1, 26) = 0.16, p = 0.69, R^2 = -0.032$) or accuracy ($F(1, 29) = 3.25, p = 0.08, R^2 = 0.07$; Figure 5). Finally, openness to experiences was not significantly correlated with preferences ($F(1, 26) = 1.24, p = 0.28, R^2 = 0.0087$) but did show a significant correlation with accuracy, with higher openness associated with decreased accuracy ($F(1, 29) = 5.28, p = 0.03, R^2 = 0.12$; Figure 6). This analysis found no significant correlations between personality traits and preferences or accuracy in identifying AI versus human-composed music, except that higher openness was linked to decreased accuracy.

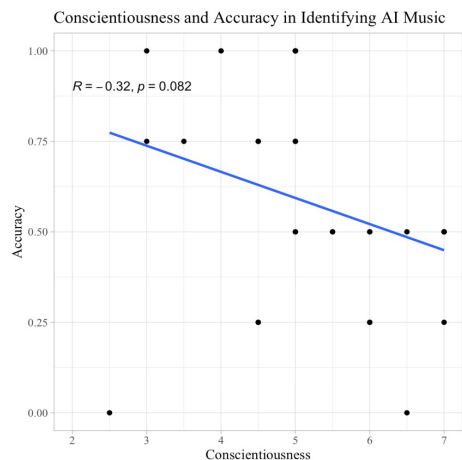


Fig. 5 Negative Insignificant Correlation: Conscientiousness and Accuracy

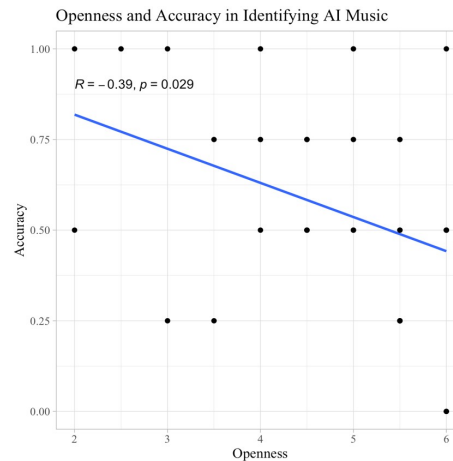


Fig. 6 Negative Correlation: Openness and Accuracy

Discussion

Aim 1: Human Bias Against AI-generated Music

This study replicated previous findings on the existence of people's preferential bias towards human-made art, with a unique focus on musical works^{10,15,16}. This result furthers our understanding of the intricate relationship between individual characteristics with the perception of AI's creative outputs.

This study has observed a significant difference between the ratings for music perceived to be composed by AI versus the ratings for music perceived to be composed by humans. Furthermore, the moderately large effect size calculated for the results of perceived authorship was greater than that of actual authorship, suggesting that regardless of AI's actual competency as a composer, people's perception played an important role in their preference. A possible explanation of the differences in preferences is that there may be noticeable differences between music composed by humans and AI, such as AI's lack of ability to create complex melodic or harmonic structures, as well as a lack of emotional depth. A possible explanation of this is likely due to its inferior compositional understanding and its repetitive quality contributing to its lack of originality²⁰, which is often emphasized in determining the emotional and cultural value of a musical piece²¹.

Yet as recent studies suggest, this gap has been significantly narrowed^{13?}. Furthermore, the larger difference in ratings between music perceived to be composed by AI or humans regardless of the actual authorship suggests that naturally occurring anthropomorphic biases may affect the listener's perception of music¹¹. For instance, a study by Hong et al. concluded that when participants were presented with anthropomorphic characteristics of a music-generating artificial intelligence, such as humanlike interface or qualities, the system is more likely to be accepted as a legitimate musician regardless of its creative

autonomy²². Furthermore, scholars suggest that a machine that possesses a human-like quality can invoke a sense of intimacy, self-congruency, and familiarity within the users, who are therefore likely to be favorably biased^{23,24}. Hence, when users perceive that a music piece does not sufficiently reflect human-like emotional depth and sentience, they are less likely to favor them. Such anthropomorphic bias is likely to have influenced the participants' ratings on excerpts perceived to be generated by AI.

The reason behind the bias is further explained by the responses that participants gave when asked why they marked the music to be AI or human. Human-composed music was correlated with keywords such as “emotional”, “dynamic”, or “natural”, whereas AI-generated music was described as “monotonous”, “simple”, or “lacking originality” – suggesting that participants may have underestimated the level of complexity of music that AI can compose, while inherently associating more complex compositions with humans.

As explained in the exploration of previous literature on the role of humans in music, music extends beyond its aesthetic value and into a socio-cultural medium of connection stemming from the relatability and emotional resonance of the music. Furthermore, human composers infuse their own personal experiences and emotions in their music^{25,26}; past studies on the topic suggest that this presence of “humanness” may be lacking in computer-generated music^{27,28}.

Aim 2: Demographic Characteristics & the Ability to Distinguish AI-generated Music

None of the demographic variables showed significant correlations with either accuracy or preferences. This was contrary to our first hypothesis (H1) that younger people will be able to distinguish between AI-generated music and human generated music better than older generations. Interestingly, this result contradicts previous findings on visual arts¹⁴, suggesting grounds for future research on the possible differences in responses to AI-generated art depending on the art form. This might be due to the differences between the mechanism of visual and auditory processing, where visual sensories are subject to faster aging compared to auditory sensories—resulting in more drastic differences between age groups²⁹. Another possible explanation is that one's ability to accurately distinguish AI-generated music and their preferences are developed from a collection of factors such as age, familiarity with technology, and music exposure rather than from a single factor.

Furthermore, familiarity with technology may not have influenced accuracy, as knowing how AI mimics human creativity might not correlate to recognizing musical structures that are unique to humans. Similarly, people who are more frequently exposed to music might not be able to differentiate the uniqueness of human-composed music from AI-generations due to

varying levels of knowledge on music composition. Furthermore, the choice of genre might have affected their expertise in other styles of music.

Aim 3: Personality Traits and Responses to AI-generated Music

Contrary to our second hypothesis (H2), people who score high on openness and agreeableness did not show any significant preference for AI generated music. Similarly, contrary to our third hypothesis (H3), people who score high on neuroticism and conscientiousness did not show any significant bias against AI generated music. Agreeableness, neuroticism, and conscientiousness were also unrelated to accuracy of identifying the composers. The lack of significant correlations found could be attributed to inaccuracy or dishonesty, as there is an inherent limit of collecting personality traits via self-report³⁰. Nonetheless, this finding that personality traits may not influence the perception of AI-generated music contradicts the previous study conducted on visual arts¹⁴, suggesting another possibility that there may be a difference in perception between visual arts and music.

However, part of our second hypothesis was confirmed by data. Specifically, openness and accuracy showed a negative correlation, such that people who scored higher on openness were less accurate in determining the authorship of the music excerpts. A possible explanation for this result is that people who have an exploratory and open attitude towards new experiences may have accumulated diverse experience and knowledge including music and AI without prejudice, which may have given them a disadvantage in recognizing the difference between musical traits inherent to humans versus AI. In different contexts, literature suggests that individuals with high openness may show poorer decision-making skills with intuition-based tasks or rely more on predictive imagination as opposed to fluid intelligence, all of which might account for decreased critical assessment abilities^{31,32}. However, there are also contrasting findings that suggest that high openness positively influences auditory discriminative ability in music and better critical discriminative abilities in general^{33,34}. Therefore, the relationship between openness to experience and discriminative abilities between human-composed music from AI-composed music is still yet to be further explored.

The nonsignificant findings also point to an important discussion about the role of different personality traits specifically on music perception. For instance, there have been mixed research outcomes on the relationship between conscientiousness and the ability to discriminate between human and AI-generated music. Some studies suggest that conscientious individuals are more likely to base their decisions on internal consistency and preceptual assumptions, decreasing their adaptability and performance accuracy in subjective tasks^{35,36}. However, this explanation is

directly opposed to other studies that show that conscientiousness is positively correlated with accuracy in identification of AI music, due to the attentive and observant trait associated with conscientiousness that better allow them to spot unique characteristics and discrepancies³⁷. Therefore, the specifics of how each personality trait – such as conscientiousness and openness – influence people’s perception of AI-generated art remains to be explored in more detail.

Explaining Contradictions with Previous Literature

This section aims to further explore the possible explanations behind the hypotheses that were not supported by this data. Firstly, our study had a relatively small sample size ($n=31$), which limits the statistical power to detect significant correlations. Previous studies with larger samples may have been more capable of identifying such relationships. Due to recruitment and time limitations, we also used a 10-item version of the Big-5 personality exam. The full-length version of the test would have provided more accurate analysis of each individual’s personality.

Another possible explanation is that personal traits might be less of a discriminating factor in aural stimuli. This is further supported by the fact that the study did find significant correlation between the preferences towards AI-generated and human-composed music, but didn’t find discriminating factors in personal attributes of people that influenced their preference of AI-generated music. Ultimately, the contradictions found in the results point to the possibility that studies on auditory art may show different results than studies on other types of art, consequently pointing to a need for more large-scale studies focused specifically on auditory stimuli such as music.

Despite these limitations, this study is meaningful in that it is one of the first studies to focus on personal traits and perception towards AI-generated music. It not only was able to replicate past literature on the negative perception towards other types of AI-generated art, but it also provided further evidence that this bias may exist regardless of individuals’ personal traits. Therefore, this study provides a potential direction for future researchers to focus on AI systems that are universally appealing, and to explore the factors that can explain the difference in people’s perception of different domains of sensory stimuli.

Limitations and Future Directions

There are several limitations to the current study. First, online surveys are naturally prone to errors and incomplete responses³⁸. Although a reCAPTCHA item and an attention check question were added in the questionnaire in order to ensure the validity of the data, 44 out of 75 responses still had to be excluded from analyses. Second, the ten-item personality measure questionnaire may fail to provide as much accuracy as the full-length Big 5 personality test³⁹. Therefore, a full-length physical survey

would be a better alternative for future studies. Lastly, the relatively small sample size ($n=31$) may have affected the validity and generalizability of the results⁴⁰. Different results may have been obtained with a larger sample size.

Despite these limitations, the present study replicated findings about anthropomorphic biases that humans have when evaluating AI-generated works^{11,12}. In other words, participants were more prone to consider works perceived to be composed by humans to be of higher value while thinking of the contrast as for works perceived to be generated by AI. In addition, this study identified a larger difference in ratings based on the perceived rather than the actual composer, suggesting that one’s internal, subjective bias influences their evaluation of AI music more than the actual differences in the quality of music. Furthermore, results suggest a possible difference between the factors that influence the perception of music and other art forms including visual arts. Future studies comparing different art forms in a controlled environment may provide further understanding into people’s perception of AI-generated artworks. Lastly, the relationship between accuracy in identifying AI-generated artwork with openness and conscientiousness – as well as other personality characteristics – remains a topic to be further explored.

The findings of this study, along with previous research on the field, underscore the prevailing skepticism surrounding the integration of AI within creative domains, and perhaps in other domains as well. They also highlight the complex nature of our perception of AI generated artwork, suggesting that a single demographic or personality trait may not be a sufficient explanation of our attitudes. As per the Technology Acceptance Model (TAM)⁴¹, it is crucial for a system to not only be perceived useful or be easily usable, but also for the users’ attitude towards the technology to be positive for the system to be actually put in action. Therefore, in light of the growing interest in the coexistence of humanity and AI, research in this area is crucial to help enhance the adaptation of AI in various domains and bridge the current disparity.

In the process of doing so, further research in how AI is perceived in society is imperative in enriching the ongoing debate on AI ethics regarding the authenticity of its creative works⁴², such as whether the system deserves a proper attribution, or the exploration of alternative ways AI can assist humans instead of replacing them as a whole. For instance, an improved perception of AI-generated music might allow smoother integration of AI as a collaborative tool that shares partial attribution to the human artist.

Addressing these issues while improving the appeal of artificial intelligence systems can ultimately inform future developers and distributors to effectively integrate music generative services into various fields beyond music that could benefit from AI’s capabilities of music creation, such as therapy^{43,44}, education⁴⁵, and media^{46,47}. By understanding how various people react to AI-generated music and perceive it, this research serves as a

catalyst for ongoing dialogue, finding ways to effectively target audiences and encourage a more nuanced understanding of AI's role in art and music.

Methods

Procedures

The study was conducted for a duration of 33 days. Data was collected in April (n = 74) and May (n = 1) of 2024, with the start and end dates of April 3rd to May 5th. There were no follow-up surveys. This study was an online survey administered via Qualtrics. Informed consent was obtained electronically at the beginning of the survey. The questionnaire began by surveying basic demographic information, including age, sex, nationality, exposure to music, and familiarity with technology. Participants were then randomly distributed into either group A (n=18), presented with excerpts in the style of classical music, or group B (n=13), presented with excerpts in the style of contemporary pop music. Participants were then presented with randomly ordered 2 AI-generated and 2 human-made music excerpts ranging from 20-30 seconds. The AI-generated music excerpts were adopted from the AI tool AIVA with permission. After listening to each music piece, participants are asked to rate their preference for the music in a 7 point Likert scale⁴⁸. Participants then completed a 10-item questionnaire examining their Big 5 personality traits⁴⁹.

Social media platforms such as Instagram were used for advertising the survey. Physical flyers were also posted in locations of Seoul, South Korea and Philadelphia, PA, United States. Only adults over the age of 18 were targeted for the purpose of the survey.

Analysis

Preferences of music based on the actual or perceived authorship were analyzed using two pairwise t-tests comparing the average ratings of music based on actual and perceived authorship in order to best capture the discrepancy between the two mean values. The relationships between continuous variables such as demographic variables, personality traits, and accuracy were calculated using linear regression models. All statistical analyses were performed in R.

Participants

There were a total of 75 responses, out of which 31 were ultimately used for data analysis. Responses were removed if they were incomplete (n=41), not consented (n=1), or failed the attention check (n=2).

Out of the 31 valid responses, there were 6 people between 18-24, 7 between 25-34, 5 between 35-44, 11 between 45-54,

and 2 in 55+ range. In addition, there were 19 females and 12 males. Respondents' nationalities included Canada (n=1), China (n=1), Myanmar (n=1), Philippines (n=1), South Korea (n=24), Timor-Leste (n=1), United States (n=2; Table 1).

Table 1. Demographics

Characteristic	Female, N = 19 ⁱ	Male, N = 12 ⁱ
Age		
18-24	3 (16%)	3 (25%)
25-34	4 (21%)	3 (25%)
35-44	3 (16%)	2 (17%)
45-54	8 (42%)	3 (25%)
55+	1 (5.3%)	1 (8.3%)
Nationality		
Canada	1 (5.3%)	0 (0%)
China	1 (5.3%)	0 (0%)
Myanmar	1 (5.3%)	0 (0%)
Philippines	1 (5.3%)	0 (0%)
South Korea	12 (63%)	12 (100%)
Timor-Leste	1 (5.3%)	0 (0%)
United States of America	2 (11%)	0 (0%)
ⁱ n (%)		

Exposure to Music was measured in hours per day including time spent listening, making, or playing music. One response (30 hours) was removed from the summary statistics due to infeasibility. The mean was 3.03 and the median was 2. Familiarity to technology and AI in general was measured on a 1-10 scale. The mean was 4.17, and the median was 4 (Table 2).

Table 2. Summary Statistics of Baseline Characteristics

Statistic	N	Mean	St. Dev.	Min	Median	Max
Exposure to Music	30	3.027	2.688	0.000	2.000	10.000
Familiarity with Technology	30	4.167	2.086	1	4	10

Materials

Music Excerpts

The 4 AI-generated music excerpts were adapted with permission from publicly available music uploaded on YouTube by the Luxembourg startup AIVA technologies that featured their AI tool AIVA (Artificial Intelligence Virtual Assistance)'s compositions. AIVA generates music by formulating a mathematical deduction of musical rules from a matrix representation of musical excerpts in a given style, which is later applied during its

compositional process. Similar to other commercially available music generating AI, AIVA is an autonomous agent that outputs new compositions without direct human input⁵⁰.

Multiple musical genres were considered for the purposes of this study, as music genres have distinct features which appeal to different groups of audience⁵¹. Therefore, to prevent possible biases and to maximize the reliability in the findings of this study, a wide range of genres were adapted in the survey. The chosen genres were mainly divided into classical and contemporary music, driven by an informal pilot interview ($n=5$), where volunteer participants with a range of musical backgrounds were asked to identify distinct genres of music that would be most appropriate for the purposes of this study.

The classical pieces included “Romanticism in D minor” and “Nocturne in C# minor”, each in the style of an orchestral symphony and a piano solo from the romantic era, respectively. The contemporary pop songs included “All Night Beach Party” and “Daiquiri”, each in the style of electronic dance music and jazz respectively.

The human-composed classical pieces were “Symphony No.1 in C minor” and “Nocturne No.13 in D minor” respectively composed by Antonio Dvorak and John Field, in the style of a romantic symphony and a piano nocturne for consistency. The contemporary pop pieces were “Cuenta ” and “Flower” respectively by Autohacker and MetzMusic, also publicly uploaded onto YouTube. These were also in the style of electronic dance music and jazz.

All of these pieces lasted from the beginning to the 30 to 45-second mark into the music; the mean duration of the excerpts being 36.25 seconds. This range was adapted from an estimate from past literature. For example, Zenieris used 45 seconds, and Zlatov et al used 10 seconds; however, there were 10 excerpts that the participants had to listen to. Furthermore, 30-45 seconds was an appropriate duration for participants to not lose attention listening to music⁵².

Big-5 Personality Traits

Along with their choices for the identities of the composers and their preferences for the music excerpts, the participants were also asked to complete a condensed 10-item version of a Big-5 personality trait form²⁰. The types of questions asked required the participant to rate how much they thought the two descriptive words given matched their personality on a scale of 1-7. The results of the survey determined one’s personality characteristics on 5 domains: conscientiousness, openness, extraversion, neuroticism, and agreeableness.

The decision to use the abbreviated version of the Big-5 personality form was mainly due to time constraints, given that this survey was distributed online without any compensation. As the full length version has 44 items, it is likely to take a minimum of an extra 10-15 minutes to complete, which would be a barrier in recruitment and retention – especially considering

the combined length of the entire survey.

Conclusion

In this study, we explored how personal attributes of an individual affects their ability to accurately discriminate between AI- and human-generated musical pieces, and their musical preferences based on whether they thought it was generated by an AI or not. We recruited 31 participants to participate in a volunteer-based survey, which included 4 excerpts in two different genres and a 10-item big 5 personality test at the end. Our findings showed that there was a significant correlation between people’s perception of the authorship of the music piece and their ratings of the music, in which people were more likely to give lower ratings to pieces that they thought were composed by AI. Additionally, we also found that on average, people’s ability to accurately infer the authorship of a musical piece was only slightly over chance, meaning that perceived authorship may influence people’s perception regardless of the actual accuracy in their judgment. Lastly, we found no significant correlations between personal traits and discriminative abilities nor preference, albeit some exceptions explained in previous sections.

Amidst the growing expectations for music generative AI, there has been increasing interest in and controversy around the integration of the technology in art and its ethical usages. In the status quo, AI-generated music is not yet capable of completely replacing human-composed music—the reason for which is supported by previous literature on the unique role of humans in art and the limit of AI-generated music as a medium of expressing musical depth. Due to this limitation, individuals generally formulate a negative perception of AI-generated music. This study aimed to further our understanding on the complex relationship between humans and AI generated music by investigating how personal characteristics affect people’s discriminative abilities when it comes to musical authorship, as well as their perception and preferences on the output. It also expanded the scope of the literature on AI generated art and personal traits to auditory art. The results of this study can serve as a useful foundation for further research on AI-generated music and ultimately contribute to a more successful integration of AI into various creative domains.

References

- 1 J. Schulkin and G. B. Raglan, *The evolution of music and Human Social Capability*, <https://doi.org/10.3389/fnins.2014.00292>.
- 2 G. F. Welch, *Editorial: The impact of music on human development and well-being*, <https://doi.org/10.3389/fpsyg.2020.01246>.
- 3 P. E. Savage, *Music as a coevolved system for social bonding*, <https://doi.org/10.1017/s0140525x20000333>.
- 4 B. Bogunović, *Creative cognition in composing music*, <https://doi.org/10.5937/newsol1901089b>.

- 5 M. Boden, *Creativity and artificial intelligence*, [https://doi.org/10.1016/s0004-3702\(98\)00055-1](https://doi.org/10.1016/s0004-3702(98)00055-1).
- 6 Z. Epstein and A. Hertzmann, *Art and the science of generative AI*, <https://doi.org/10.1126/science.adh4451>.
- 7 N. Anantrasirichai and D. Bull, *Artificial intelligence in the creative industries: A review*, <https://doi.org/10.1007/s10462-021-10039-7>.
- 8 *MuseNet, OpenAI*, openai.com/index/musenet.
- 9 C.-Z. A. Huang, *Music transformer*, arXiv preprint (2018). arXiv:1809.04281.
- 10 M. Ragot, N. Martin and S. A.-g. Human Artworks, Extended Abstracts of the 2020 CHI Conference on Human Factors in Computing Systems, p. 1–10.
- 11 R. Chamberlain, C. Mullin and J. Wagemans, *The artistic Turing test: An exploration of perceptions of computer-generated and man-made art*, <https://doi.org/10.1167/15.12.112>.
- 12 R. Chamberlain, C. Mullin, B. Scheerlinck and J. Wagemans, *Putting the art in artificial: Aesthetic responses to computer-generated art*, <https://doi.org/10.1037/aca0000136>.
- 13 H. Gangadharbatla, *The role of AI attribution knowledge in the evaluation of artwork*, <https://doi.org/10.1177/0276237421994697>.
- 14 S. Grassini and M. Koivisto, *Understanding how personality traits, experiences, and attitudes shape negative bias toward AI-generated artworks*, <https://doi.org/10.1038/s41598-024-54294-4>.
- 15 U. Agudo, M. Arrese, K. Liberal and H. Matute, *Assessing emotion and sensitivity of AI artwork*, <https://doi.org/10.3389/fpsyg.2022.879088>.
- 16 H. Chu, J. Kim, S. Kim, H. Lim, H. Lee, S. Jin, J. Lee, T. Kim and S. Ko, Proceedings of the 31st ACM International Conference on Information Knowledge Management, p. 304–314.
- 17 F. Moura and C. Maw, *Artificial intelligence became Beethoven: How do listeners and music professionals perceive artificially composed music?*, <https://doi.org/10.1108/JCM-02-2020-3671>.
- 18 Y. Zhang and R. Gosline, *Human favoritism, not AI aversion: People's perceptions (and bias) toward generative AI, human experts, and human-GAI collaboration in persuasive content generation*.
- 19 D. Shank, C. Stefanik, C. Stuhlsatz, K. Kacirek and A. Belfi, *AI composer bias: Listeners like music less when they think it was composed by an AI*, <https://doi.org/10.1037/xap0000447>.
- 20 Z. Yin, F. Reuben, S. Stepney and T. Collins, *Deep learning's shallow gains: A comparative evaluation of algorithms for Automatic Music Generation*, <https://doi.org/10.1007/s10994-023-06309-w>.
- 21 A. Jordanous, *A standardised procedure for evaluating creative systems: Computational Creativity Evaluation based on what it is to be creative*, <https://doi.org/10.1007/s12559-012-9156-1>.
- 22 J.-W. Hong, K. Fischer, Y. Ha and Y. Zeng, *I wrote a Song For You: An Experiment Testing the influence of machines' attributes on the AI-composed music evaluation*, <https://doi.org/10.1016/j.chb.2022.107239>.
- 23 A. Alabed, A. Javornik and D. Gregory-Smith, *AI anthropomorphism and its effect on users' self-congruence and self-AI integration: A theoretical framework and research agenda*, <https://doi.org/10.1016/j.techfore.2022.121786>.
- 24 Y. Xie, K. Zhu, P. Zhou and C. Liang, *How does anthropomorphism improve human-ai interaction satisfaction: A dual-path model*, <https://doi.org/10.1016/j.chb.2023.107878>.
- 25 S. Stauffer, *Connections between the Musical and Life Experiences of Young Composers and Their Compositions*, <https://doi.org/10.2307/3345357>.
- 26 W. Thompson and B. Robitaille, *Can Composers Express Emotions through Music?*, <https://doi.org/10.2307/3345357>.
- 27 N. Ziv and O. Moran, *Human versus Computer: The Effect of a Statement concerning a Musical Performance's Source on the Evaluation of its Quality and Expressivity*, <https://doi.org/10.2190/E4EN-1X32-KUU1-LDHT>.
- 28 P. Nguyen, *Naturalistic and non-naturalistic renderings in new music*, <https://doi.org/10.1016/j.yjoc.2024.100084>.
- 29 R. Čepionienė, M. Westerfield, M. Torki and J. Townsend, *Modality-specificity of sensory aging in vision and audition: Evidence from event-related potentials*, <https://doi.org/10.1016/j.brainres.2008.02.010>.
- 30 F. Lang, D. John, O. Lüdtke, J. Schupp and G. Wagner, *Short assessment of the Big Five: Robust across survey methods except telephone interviewing*, <https://doi.org/10.3758/s13428-011-0066-z>.
- 31 C. Newton, J. Feeney and G. Pennycook, *On the Disposition to Think Analytically: Four Distinct Intuitive-Analytic Thinking Styles*, <https://doi.org/10.1177/01461672231154886>.
- 32 E. Nusbaum and P. Silvia, *Are openness and intellect distinct aspects of openness to experience? A test of the O/I model*, <https://doi.org/10.1016/j.jpaid.2011.05.013>.
- 33 K. Thomas, P. Silvia, E. Nusbaum, R. Beaty and D. Hodges, *Openness to experience and auditory discrimination ability in music: An investment approach*, <https://doi.org/10.1177/0305735615592013>.
- 34 M. Abu Raya, A. Ogunyemi, J. Broder, V. Carstensen, M. Illanes-Manrique and K. Rankin, *The neurobiology of openness as a personality trait*, <https://doi.org/10.3389/fneur.2023.1235345>.
- 35 Y. Singh, M. Adil and S. Haque, *Personality traits and behaviour biases: the moderating role of risk-tolerance*, <https://doi.org/10.1007/s11135-022-01516-4>, Advance online publication (2022).
- 36 A. Koriat, *Subjective confidence in perceptual judgments: A test of the self-consistency model*, <https://doi.org/10.1037/a0022171>, 2011a).
- 37 V. Swift, K. Wilson and J. Peterson, *Zooming in on the attentional foundations of the Big Five*, <https://doi.org/10.1016/j.jpaid.2020.110000>.
- 38 M. Ward and A. Meade, *Dealing with Careless Responding in Survey Data: Prevention, Identification, and Recommended Best Practices*, <https://doi.org/10.1146/annurev-psych-040422-045007>.
- 39 A. Lovik, G. Verbeke and G. Molenberghs, *Evaluation of a very short test to measure the Big Five Personality Factors on a Flemish sample*.
- 40 L. Evans and M. Buehner, *Small samples do not cause greater accuracy—but clear data may cause small samples: comment on Fiedler and Kareev (2006)*.

-
- 41 I. Gogan, E. Matemba, G. Li and B. Maiseli, *Technology acceptance model: Recent developments, Future Directions, and proposal for Hypothetical Extensions*, <https://doi.org/10.1504/ijtip.2020.10032142>.
- 42 R. Battle-Roca, *Transparency in Music-Generative AI: A Systematic Literature Review*, <https://doi.org/10.21203/rs.3.rs-3708077/v1>.
- 43 D. Williams, V. Hodge and C.-Y. Wu, *On the use of AI for generation of functional music to improve mental health*, <https://doi.org/10.3389/frai.2020.497864>.
- 44 Y. Chen, L. Huang and T. Gou, *Applications and Advances of Artificial Intelligence in Music Generation: A Review*, arXiv preprint (2024). arXiv:2409.03715.
- 45 *IOP Conf*.
- 46 M. Civit, J. Civit-Masot, F. Cuadrado and M. Escalona, *A systematic review of artificial intelligence-based music generation: Scope, applications, and future trends*, <https://doi.org/10.1016/j.eswa.2022.118190>.
- 47 C. Plut and P. Pasquier, *Generative Music in Video Games: State of the art, Challenges, and prospects*, <https://doi.org/10.1016/j.entcom.2019.100337>.
- 48 D. Zlatkov, J. Ens and P. Pasquier, *Searching for human bias against AI-composed music*, https://doi.org/10.1007/978-3-031-29956-8_20.
- 49 B. Rammstedt and O. John, *Measuring personality in one minute or less: A 10-item short version of the Big Five Inventory in English and German*, <https://doi.org/10.1016/j.jrp.2006.02.001>.
- 50 A.I.V.A., *About aiva*, <https://www.aiva.ai/about>.
- 51 P. Rentfrow, L. Goldberg and D. Levitin, *The structure of musical preferences: a five-factor model*, <https://doi.org/10.1037/a0022406>.
- 52 P. J. Flowers, *Patterns of Attention in Music Listening*, <http://www.jstor.org/stable/40319077>.