Dimensions on the Perception of Users Towards AI Generated Music

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Abstract. *Music-generating Artificial Intelligence has reached a point where anyone, musician or not, can generate full-length songs from a simple textual query. As with other recent AI advances, such services are poised to impact various sectors of arts and industry, sparking social debate about their role in our daily lives. In this paper, we investigate the question: How do musicians and non-musicians perceive AI-Generated Music (AGM) services as a tool? We conducted a user-centered study (N=96) exploring perceptions of AGM in composition, production, education, and its ethical implications. The research is based on a quantitative survey analyzed using Exploratory Factor Analysis and Latent Profile Analysis, complemented by a thematic analysis of open-ended responses. Overall, results indicate a positive trend in opinions towards AGM for composition and production. The Latent Profile Analysis reveals two distinct participant groups. The larger group (77%) is highly enthusiastic about AGM for composition and production and also holds a more optimistic view of its ethical and cultural implications. The smaller group (23%) is broadly skeptical, holding a negative view of AGM's compositional, production, and ethical aspects. Notably, both groups acknowledge the potential of AGM in education. This finding supports AGM as a promising tool for democratizing music composition and education.*

1. Introduction

The growing use of Artificial Intelligence (AI) in music[1] has generated both possibilities and challenges for composers, producers, and researchers alike. In particular, AI enables the exploration of innovations in music creation and production [1]. However, this emerging landscape raises critical questions regarding the ethical, creative, and educational implications, which are still not fully understood. This highlights a common challenge across the field of generative models – the inherent difficulty in understanding how they will impact different sectors [2].

Returning our focus to AI-Generated Music (AGM), tools like Suno[2] are capable of producing a complete piece of music that sounds as if composed by a human in seconds [3]. While several previous efforts have either focused on developing models for AGM [4, 5, 6] or evaluating AGM quality [3, 7], further studies are needed to foster discussions and provide access to the general community about the impacts of such tools in this rapidly growing field. Some authors have shown considerable resistance to the use of AI in music production due to the concern that AI may erase traces of marginalized cultures, as the representative models used by most researchers fail to account for fundamental elements of music from non-hegemonic populations [8].

In a similar tone, other studies have pinpointed that contextual information can shape aesthetic judgments of artistic productions, meaning that knowing a product was created by AI influences the assessment of its quality [7]. These are examples of studies that show a critical view of AGM. In a broader sense, beyond music, there is growing concern about jobs being superseded by AI [2].

Debates such as the ones we have cited are the motivators of our work, which takes a complementary view **to** the aforementioned literature. In particular, we focus on understanding how end users (here called participants) perceive such services with regard to their composition process by asking the question of *How do participants perceive AGM services as a tool?* To summarize, the present study aims to examine the latent participant dimensions of AGM acceptance in the musical context.

To perform our study, we resorted to an opinion survey that was answered by 96 participants. Before sending our survey to these participants, a panel of experts discussed and evaluated the questions that would compose the survey. In the end, 17 questions covered 9 different themes: *1. Quality of AI-generated music; 2. Inspiration and Overcoming Creative Blocks; 3. Integration of AI in the Creative Process; 4. Efficiency and Innovation in the Composition Process; 5. Impact on the Music Industry and Democratization; 6. Music Education and Accessibility; 7. Preservation and Cultural Relevance; 8. Specific Applications of AI in Music; and 9. Ethics and Originality.*

Observe that the themes encompass diverse musical concepts. Thus, we attempted to gather responses from both individuals with musical experience and education, as well as unexperienced participants. Responding participants were recruited either via a snowball [9] method starting from the Music Department of our university. 50% of respondents stated having over five years of formal musical education, 12% between one to five years, and 38% less than one year.

[1]https://tinyurl.com/3nnbyjtp
[2]https://suno.ai

To present our results, we explore both quantitative and qualitative methods. Focusing on the quantitative aspect, we delve into the Psychometric literature and resort to Exploratory Factor Analysis (EFA), as well as Latent Profile Analysis (LPA). Our results indicate that participants fall into two distinct groups. The first and larger group, comprising 77% of respondents, is more enthusiastic about AGM in composition and production and also holds a more optimistic view of its ethical implications. The second, smaller group, with 23% of participants, holds a generally negative and skeptical view of AGM across compositional, production, and ethical dimensions. Despite these differences, both groups express some support for the use of AGM in educational contexts. On the qualitative aspect, one open-ended participant response item was grouped using open coding. These results support our quantitative analysis and provide an in-depth look into participant opinions.

While prior studies have explored perceptions of AI-generated music, our contribution lies in applying rigorous quantitative psychometric analysis complemented by qualitative thematic exploration, providing nuanced insights into existing debates rather than wholly novel findings. In this sense, we are the first work to present a user-based study of AGM on this scale and with the aforementioned methods.

2. Related Work

The assessment of participant perception regarding the production of AGM, whether from composers or the general public, is a concern of the MIR community. Studies involving legal issues [10, 11], human-computer interaction [12, 13] and the use of technology in music production [14, 15] can be found in the literature, although most of these efforts focus on **evaluating the aesthetics** of the generated works [10, 16, 17, 18]. In this regard, opinions tend to be polarized between supporters of the use of AI in music and skeptics or opponents of this trend.

Qualitative or quantitative studies generally analyze small groups of participants with homogeneous profiles, whether composers, listeners of a certain musical genre, or fans of specific musicians. Investigating the acceptance of AGM by composers, Newman et al. [19] presented a case study based on the perception of 6 composers about the impact of AI on the creative process through semi-structured interviews, revealing concerns about transparency and lack of control in collaborative tools. Similarly, Tchemeube et al. [20] analyzed the acceptance of the Multi-Track Music Machine tool in a group of 18 composers, where factors related to usefulness and ease of use were evaluated. The results demonstrated positive experiences of usability and acceptance, although there were reports of limitations in the controllability and predictability of the interface.

Regarding the perception of the general public, Chu et al. [21] analyzed the satisfaction of 100 participants with automatic symbolic music generation based on nine evaluation metrics related to collected subjective criteria, including creativity, naturalness, richness, rhythmicity, structure, and coherence. Still aiming to study the acceptance of AI music in the development of the music industry, Li et al. [22] used questionnaires applied to a group of young fans of the singer JJ Lin. The research revealed, at the same time, an acknowledgment of the aspects of innovation and diversity, concerns about emotional expression, social responsibility, and issues related to copyright. More recently, Prassetyo et al. [23] investigated the perception of a group of 48 students of a language course while using Suno to compose nursery songs. The study indicated positive views regarding ease of use, efficiency, and ability to inspire creativity.

Within the reviewed literature, the study that most closely resembles our approach is the survey presented by Correia [24] on public acceptance of AI in musical composition. However, Correia [24] does focus mostly on two aspects: the openness of participants towards AGM and the prior usage of such tools.

Overall, a gap still exists in the focus of our work: a larger-scale quantitative study on how participants perceive AGM. In particular, our study focuses on nine aspects of AGM. More importantly, we explore concepts such as Exploratory Factor Analysis and Latent Profile Analysis, tools from Psychometrics developed specifically to uncover patterns of human responses from studies as our own.

3. Materials and Methods

We began our research with a discussion within our lab on the possible gaps in participant opinions regarding AGM. Four professors—three from Computer Science and one from the Music Department—and a postdoctoral researcher from the Music Department spearheaded these discussions. Graduate and undergraduate students from the lab were also encouraged to take part in these initial discussions and share their opinions. From these debates, we created our questionnaire, which is described next.

3.1. Materials

From the initial debate, a survey of 36 statements (or items) was drafted. These items covered the themes of: *1. Quality of AI-generated music; 2. Inspiration and Overcoming Creative Blocks; 3. Integration of AI in the Creative Process; 4. Efficiency and Innovation in the Composition Process; 5. Impact on the Music Industry and Democratization; 6. Music Education and Accessibility; 7. Preservation and Cultural Relevance; 8. Specific Applications of AI in Music; and, 9. Ethics and Originality.* For each theme, 4 statements were drafted, totaling 36.

Four judges, who did not take part in drafting the statements, evaluated each item. This evaluation consisted of two ratings per item, one rating for textual clarity and a second rating for pertinence to the subject of study. Answers were submitted on a 5-point Likert scale: *Strongly Disagree, Disagree, Neutral, Agree, Strongly*

Item ID	Statement
I1	AI tools facilitate the music composition process.
I2	AI tools can help overcome creative blocks in music composition.
I3	AI tools can help explore new musical styles and genres.
I4	AI can accelerate the development of new compositions and optimize music production time.
I5	AI tools can collaborate in creating complex musical arrangements.
I6	AI tools can make music production more accessible to people without technical training.
I7	AI tools can help democratize music production.
I8	AI can be a useful tool for musical inspiration.
I9	AI can be a valuable tool for teaching music theory interactively.
I10	AI facilitates music education for people with disabilities.
I11	The preservation of traditional musical styles can be aided by AI.
I12	The promotion of musical diversity is facilitated by the use of AI.
I13	AI can help create soundtracks for films and games.
I14	AI can be used to remaster old music.
I15	AI can create music that is truly original and not just a combination of existing works.
I16	The use of AI in music composition can lead to issues of plagiarism and copyright.
I17	Ethical creation of music with AI can be achieved without unduly exploiting the work of human composers.

Table 1: Statements on the Survey.

Agree. Judges could also provide textual feedback for each item.

The Content Validity Coefficient (CVC) metric [25] was used to measure agreement. CVC ranges from 0 to 1, with 0 indicating no agreement and 1 indicating total agreement. Out of the 36 initial statements, 17 were retained when thresholding with a CVC of 0.80 or above (a standard cutoff from the literature [25]). The judges' textual feedback was also considered to refine the phrasing of statements.

The final items are presented in Table 1. For each item, participants were required to respond with an agreement score to the textual statement of that item. The same 5-point Likert scale was used. After completing the survey, participants could provide open-ended answers in textual form to the question: *What else would you like to add with regards to the topic of this questionnaire?* This last question was optional, while all other items required obligatory responses. Partial responses were not considered.

Two versions of the survey were created, one in English and one in Brazilian Portuguese (the native tongue of the authors). Before answering the survey, participants were asked to share their demographic information and musical experience. The collected variables were: *Gender, Race, Age, Country, Education Level, Musical Education in Years, and Musical Practice in Years*. We also gathered a binary variable indicating whether the respondent had used a commercial tool like Suno.

From the set of demographic variables, the main explanatory ones we use in our study are: *Musical Education in Years*, *Musical Practice in Years*, *Age*, and *Prior Usage of AGM tools such as Suno*. In other words, these are the variables we use to explain results from our Exploratory Factor Analysis model. The *Gender, Race, Country, and Education Level* variables are used only to characterize our participant pool. That is, we do not expect that *Gender and Race* would have any relationship with our results. In fact, we did check and confirm this in our analysis. Regarding *Education Level*, notice how other variables, such as *Musical Education in Years*, are more closely related to our study and play a similar role.

It is important to recall that this study focuses on aspects such as musical production and composition. Although it was not a requirement to partake in the survey, we attempted to gather responses from participants with some musical experience and education. Thus, the initial participant pool was recruited from the Music Department, as well as MIR-focused mailing lists, group chats, and social media. Some initial responses also came from personal contacts not related to the study. Participants were encouraged to share the survey with their own contacts.

A total of 96 participants took part in the study. Most of these, 65%, answered the Portuguese version of the survey. Similarly, over 75% of participants were from Brazil. The remaining 25% of participants came from several countries such as Germany, USA, Belgium, Canada, China, Iran, South Korea, Poland, Spain, Sweden, among others.

Participants had an average age of 34.54 years (SD = 13.06, min = 19, max = 78). Regarding education, 9% had a high school level of education, 40% had a bachelor's degree, 24% had a master's, and 20% had a PhD. The remainder of the participants cited other education levels, such as post-graduate studies underway. With respect to gender, 70% of participants were self-declared males, whereas 27% were females, and 3% preferred not to declare their gender. Regarding race, 65% of participants declared themselves to be Caucasian, 18% considered themselves of mixed race[3], 4% Black, and 8% Asian. Others did not declare a race.

When considering musical education, answers were grouped into: No education (25%), Up to one year (13%), One to five years (12%), and Over five years (50%). A similar trend was observed for musical practice in years: No education (16%), Up to one year (9%), One to five years (13%), and Over five years (62%). Finally, approximately 46% had already generated music using AI tools.

3.2. Methods

In this study, a Mixed Methods [26] approach was used to analyze the survey answers. Multivariate statistical analysis was used in the assessment of the 5-point Likert answers, whereas Grounded Theory-based open coding was used for textual answers [27].

Regarding the statistical analysis, we conducted an Exploratory Factor Analysis (EFA) [28] aimed at evaluating the factorial structure of the responses. Due to the ordinal nature of the Likert responses, EFA exploits a Polychoric Correlation Matrix, suitable for such data [29]. The goal of EFA is to decompose this correlation matrix into independent latent factors aimed at grouping similar response patterns. This is similar to Principal Components

[3] *Pardo* is a common answer in Brazil for mixed race with darker skin.

Analysis (PCA). However, PCA enforces orthogonal components, whereas EFA enforces independent ones. In EFA, each factor captures a distinct, non-overlapping (statistically independent) source of variation in the data. PCA components may share statistical relationships. For these reasons, the psychometrics literature considers PCA factors harder to interpret in isolation.

Another important difference between PCA and EFA lies in their assumptions. PCA transforms observable variables into principal components that explain most of the variance in the data. In this context, observable variables indicate the existence of principal components, which are linear combinations of the original variables. In an opposite manner, EFA assumes the existence of latent variables that explain the variation in observable variables.

Nevertheless, to briefly summarize EFA, we start from PCA. If $\mathbf{Z}$ is a z-standardized dataset, i.e., zero mean and unit variance per data column, of shape (N, I), where N is the number of participants and I the number of items. In PCA, we have that $\mathbf{Z} = \mathbf{U\Sigma W}$ and $\mathbf{Z}^T\mathbf{Z} = \mathbf{W\Sigma}^T\mathbf{\Sigma W}^T$. $\mathbf{U}$ has shape (N, K) and captures the strength of respondents in each latent factor, whereas $\mathbf{W}$, of shape (I, K) is the strength of association for the items. These are called the principal components. $\mathbf{\Sigma}$ is a diagonal matrix of square roots of eigenvalues and is always positive.

EFA works similarly, but firstly it imposes a Polychoric structure for the correlation matrix. That is, if $\mathbf{C} = \mathbf{Z}^T\mathbf{Z}$ are the (K, K) correlations, we change the form of $\mathbf{C}$ to be Polychoric before solving for $\mathbf{W}$ and $\mathbf{\Sigma}$, via: $\mathbf{C} \approx \mathbf{W\Sigma}^T\mathbf{\Sigma W}^{T4}$. $\mathbf{W}$ enforced to have independent rows. With these matrices at hand, a solution for $\mathbf{U}$ is defined (notice how it is the only free term left).

The decision on the number of factors K is crucial for EFA. To choose this number, we resorted to Exploratory Graph Analysis (EGA) [30, 31], a method shown to be more accurate [31, 32] than alternatives. Finally, the model's adequacy is assessed using the Root Mean Square Error of Approximation (RMSEA). A common step to statistically validate EFA is Confirmatory Factor Analysis (CFA) [29]. We did perform such a step, but given that the findings were mostly similar, we omitted CFA from our results section due to space constraints.

To conclude, our final step in EFA analysis was to group participants into profiles of similar behaviors. This is called a Latent Profile Analysis (LPA). Here, we resorted to a Gaussian Mixture Model approach on the latent $\mathbf{U}$ matrix. Given that values on this matrix capture the participants' strength on each latent factor, clustering this matrix participants with similar behaviors.

Our EFA analysis was implemented in R, using the `psych` (for EFA), `cclust` (for LPA), and `EGAnet` (for EGA) packages. Analysis scripts and anonymized answers are available at `https://tinyurl.com/dimensionsAI`.

[4] In practice, this form is $\mathbf{C} \approx \mathbf{W\Sigma}^T\mathbf{\Sigma W}^T + \mathbf{\Psi}$, where the last term is a positive diagonal matrix estimated by the model. In our explanation, we decided to focus on the terms and simplified expressions that help interpret EFA results. Thus, we left this last term out for simplicity in our explanations. We also leave out implementation details.

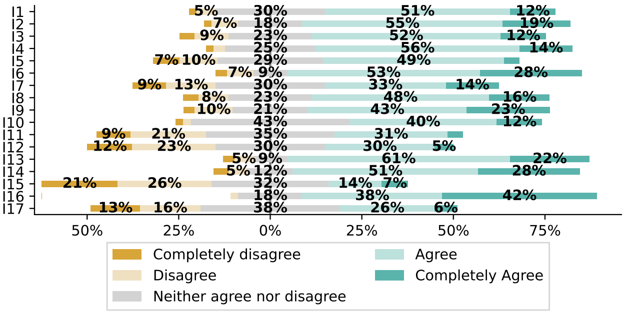

Figure 1: Summary of Responses

4. Results

In this section, we present the main findings of this study. The analysis is divided into three complementary views of the dataset: a general analysis of the responses, an EFA of the participants' perception dimensions, and an analysis of the open questions of the survey.

4.1. Overview of Responses

Figure 1 summarizes the obtained responses, showing the fraction of answers per Likert category per item. The cross-tabulation of these results with Table 1 indicates the overall trends of the respondents' opinions. Before going into individual items, the initial takeaway from the figure is that opinions generally lean toward accepting the statements. Some interesting cases are reported below.

Worries about Copyright and Plagiarism: The major exception to the positive opinions is item I15. Here, participants tend not to agree with the statement that AI tools can generate original music. Another interesting related statement is I16, where participants mostly agree that AGM leads to copyright and plagiarism issues.

Openness to AGM as a Tool for Composition: Items I1, I2, and I4 are all related to music composition and creativity. Here, participants mostly tend to agree with the statements, which points toward a positive view of AGM tools for composition. A similar item is I3, where participants also agree that AGM may help them explore new musical styles (whether for composition or not).

Democratizing Production: Moderate to strong agreement exists in items that state that AI tools make music production more accessible (I6), help democratize the process (I7), and that AI can speed up composition and production (I4).

Educational and Creative Benefits: Many respondents acknowledge that AI can inspire musical ideas (I8) and support interactive music theory education (I9). However, there is slightly less agreement regarding the use of AI for teaching music to people with disabilities (I10).

Diversity and Preservation: Respondents generally agree that AI can aid in preserving traditional music styles (I11), promoting musical diversity (I12), and remastering old songs (I14).

As a whole, these results point toward the acceptance of AI tools. In order to understand whether *Musical Education in Years* or *Musical Practice in Years* mediate such answers, we performed a chi-squared [33] test to unveil evidence of subgroups (based on these two demographic variables) with diverging answers. We also checked if the language of the survey (Portuguese v. English) led to differences. We preferred not to use the *Age* variable in this study as it is continuous. Notice how we need to stratify our dataset based on groups.

For this step, we verified if the fraction of responses for each item differed from the general results. For instance, if we consider only respondents in a certain demographic, say with more than five years of musical education, we checked whether the fraction of responses, when considering only this demographic, was statistically different from the ones shown in Figure 1.

Following the above procedure, we have three possible variables, *Musical Education in Years* (4 levels), *Musical Practice in Years* (4 levels), and *Survey Language* (2 levels), each with different possible choices, or levels (shown in parentheses). This setup leads to 10 statistical tests. Given that this is a multiple testing scenario, p-value correction was performed via the Sidak [33] method.

Out of these 10 tests, 2 cases of differences emerged when we thresholded at $p < 0.01$. Participants who had used AGM tools before, as well as respondents from the English survey, both had a more open view on the statement that AI tools can make music production more accessible to people without technical training (I6). For these two cases, Strong Agreement ranged from 32% to 38% of responses. We note that there is a correlation between both variables, as 84% of the English respondents had used such tools before. Overall, we interpret this as evidence that participants who are acquainted with such tools have a more favorable view of their potential for accessibility.

So far, we have characterized the general responses received. Nevertheless, neither the overall view of responses nor the chi-squared tests are able to understand groups of responses that relate to one another. Thus, we complement these results with the EFA, as explained next.

4.2. Exploratory Factor Analysis

Starting with the choice of the number of factors, we made use of EGA to automatically determine this value. Our EGA analysis led to a $K = 4$. This four-factor model had a $RMSEA < 10^{-4}$, indicating a very good estimation of the Polychoric correlation matrix. For the sake of comparison, if we fix $K = 1$, we reach a $RMSEA$ of 0.067. We clarify that other measures, such as the Comparative Fit Index (CFI) and the Tucker-Lewis Index (TLI) [32], also indicated that the four-factor model is more adequate.

In Figure 2, we present the four factors and their relationships. Edges in this figure are proportional to the *partial correlation coefficient*. A partial correlation coefficient tells you the relationship between two variables while controlling for the effect of other variables. Green edges indicate positive correlations, whereas red edges indicate negative ones. Zero indicates an absence of a relationship between two variables when conditioned on all others.

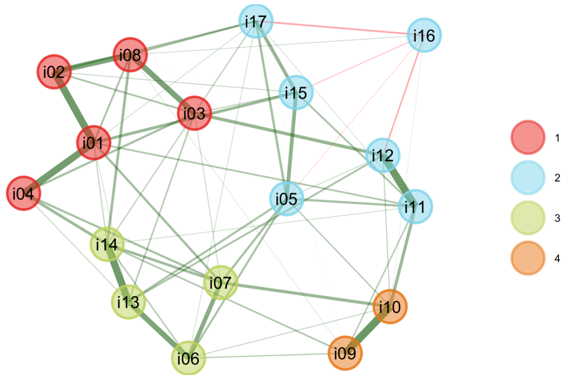

Figure 2: The relationship between the four factors (node color) extracted via Exploratory Graph Analysis (EGA). Edge weights capture the partial correlation coefficient. Green are positive correlations, red are negative ones.

	F1	F2	F3	F4
I1	0.759			
I2	0.955			
I3	0.511			
I4	0.498		0.393	
I5		0.494	0.482	
I6			0.762	
I7			0.473	
I8	0.751			
I9			0.326	0.515
I10				0.806
I11		0.650		
I12		0.721		
I13			0.800	
I14			0.650	
I15		0.495		
I16	0.325	-0.563		
I17		0.389		

Table 2: Factor structure of the EFA with 4 factors. These are the raw factor values on the $\mathbf{W}$ matrix.

In order to complement Figure 2, in Table 2, we show the actual values of the factors. This is the matrix $\mathbf{W}$ of the decomposition. It measures the strength of each item in each factor. Values close to zero, $< 10^{-3}$, were omitted.

Based on these results, we name the four latent factors as: *1) Support in Musical Composition (I1, I2, I3, I4, and I8); 2) Ethical and Cultural Optimism (I5, I11, I12, I15, I16, and I17); 3) Music Production Facilitation (I6, I7, I13, and I14); and 4) Applications in Music Education (I9 and I10).* A high score on the second factor indicates optimism, as it corresponds to agreeing that AI can be original (I15) and used ethically (I17), while disagreeing that it necessarily leads to plagiarism (I16, with its negative loading).

We now turn our attention to the $\mathbf{U}$ matrix that

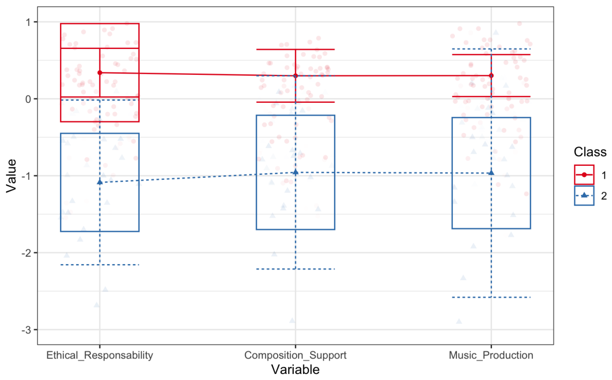

Figure 3: Results from our Latent Profile Analysis (LPA). The y-axis captures the strength of each participant on each latent factor. These are the values of the $\mathbf{U}$ matrix per participant. The latent factors are labeled on the x-axis.

summarizes participants' strengths in each factor. Initially, we explore this matrix to unveil relationships between demographic variables[5].

To perform this study, generalized linear models were used to verify which sociodemographic variables predicted the factors, and later, simple linear models were used to test which of these variables could explain the factors. In this analysis, *Age* was the only sociodemographic variable that influenced Ethical and Cultural Optimism ($p < 0.05$ and adjusted $R^2 = 0.034$). This suggests that as age increases, participants tend to be more skeptical (i.e., have lower scores on this factor). While the relationship is weak, it hints that older participants may hold more established views on authorship and intellectual property, leading to greater caution.

Finally, we conducted our Latent Profile Analysis (LPA), where we clustered the $\mathbf{U}$ matrix in non-overlapping clusters. We explored results with several numbers of clusters ranging from 2 to 10. In order to measure the quality of clustering, we resorted both to the Bayesian Information Criterion (BIC) and Akaike Information Criterion (AIC) [34]. We found that both scores deteriorate (increase significantly) after 4 clusters. Observe that this is somewhat expected as this is the exact number of latent factors found by EGA. Both BIC and AIC scores were similar for two and three clusters. In the end, when considering the choice for three clusters, we found that two of these clusters of participants overlapped visually in our next analysis. For this reason, we present results based on two clusters only.

In Figure 3, we present our LPA analysis, revealing two distinct profiles. Cluster 1, the "Enthusiasts/Optimists" (77% of participants), shows positive median values for all latent factors. This indicates a strong positive view of AGM for composition and production, coupled with optimism regarding its ethical implications. In contrast, Cluster 2, the "Skeptics" (23%), exhibits negative median values for the first three factors, indicating a negative perception of AGM's role in composition, production, and its ethical dimensions.

To further characterize these profiles, we performed a post-hoc analysis of their demographic compositions. The "Skeptics" cluster had a significantly higher average age (t-test, $p < 0.05$) and a higher proportion of participants with over five years of formal musical education (χ^2 test, $p < 0.05$) compared to the "Enthusiasts". This aligns with our linear model finding and suggests that greater experience and age may correlate with a more cautious stance on AGM.

It is noteworthy that the fourth factor, "Applications in Music Education," was the only dimension where both groups showed a positive leaning, though stronger for the Enthusiasts. This suggests a broad consensus on the value of AGM as a pedagogical tool. Even participants skeptical about its creative and ethical aspects seem to recognize its potential for facilitating learning, accessibility, and interactive education, separating its use as a support tool in a learning context from its role in professional artistic creation.

These results complement our characterization that was performed in the last subsection. While opinions lean toward agreement overall, a small but demographically distinct group of participants is more skeptical about AGM. To complement these findings, we now present our qualitative results.

4.3. Analysis of Open-Ended Questions

To complement and provide deeper context to the quantitative findings, the open-ended responses were analyzed thematically. Notably, the emergent themes strongly resonated with the latent factors identified through EFA, particularly regarding ethical concerns (F2) and the perception of AGM as a tool (F1 and F3). We identified seven primary themes. The most prevalent was "Ethical Concerns and Copyright Issues", with many participants expressing concerns about plagiarism and intellectual property. For instance, participant P0 stated: "There are very serious issues related to Ethics. One can often incur plagiarism due to ignorance - not to mention bad faith!!! - about how the app/software works and about the concept of intellectual property itself." This sentiment directly reflects the anxieties of the "Skeptic" profile. Similarly, P49 noted that "Gen AI models based on transformer models are being trained on a corpus of copyrighted data. If you prompt Suno for specific characteristics of artists it will output music which is a blatant copy."

The second significant theme was "AI as Tool versus Creator", reflecting participants' views on the appropriate role of AI in music production. Here, P26 stated: "Despite AI being a useful tool in some aspects, I don't think music should be composed by AI", while P78 elaborated: "It's a good debate, but I don't think AI should have

[5]Observe how in Table 2, the $\mathbf{W}$ matrix is mostly positive. The other model parameters (described in Section 3) are also positive. For this reason, we can interpret the sign of values in $\mathbf{U}$ as positive and negative associations. This sign indicates increases or decreases in the end results of the expression: $\mathbf{Z} = \mathbf{U\Sigma W}$ (i.e., the recomposition of the responses).

the place of composers themselves, only be a tool..." This second theme is connected closely with the third, "Quality and Authenticity of Production," where participants like P8 expressed: "I believe it can be a tool that helps many things, but at the same time it can create empty musical content..."

The fourth theme, "Educational Potential and Accessibility", highlighted AI's potential benefits in music education, with P13 suggesting that "AI can also be important to bring listeners closer to little-heard music..." This theme aligns with the broad acceptance of our fourth factor. It is also interrelated with "Research and Development Needs," as exemplified by P41: "The ideal for a country with the rhythmic and cultural diversity we have would be to train such a model here..." The remaining themes, "Workflow Integration" and "Impacts on the Creative Industry," were less prominent but still significant, with P34 noting: "AI is in an experimental phase... but I think there will be highlights... in the musical niche, which will be improved with human musical knowledge..."

5. Conclusion

This paper investigated the perceptions of musicians and non-musicians towards AGM as a tool. Our mixed-methods approach, combining a quantitative survey with qualitative analysis, identified four key dimensions in user perception: 1) Support in Musical Composition, 2) Ethical and Cultural Optimism, 3) Music Production Facilitation, and 4) Applications in Music Education.

Our primary finding is the identification of two distinct user profiles. The majority (77%) are "Enthusiasts/Optimists," who embrace AGM's potential in composition and production while being less concerned about its ethical risks. A smaller but significant minority (23%) are "Skeptics," who hold negative views across creative and ethical domains. Demographically, this Skeptic group tended to be older and have more formal musical education, suggesting that experience and established professional norms may foster a more cautious perspective. This aligns with concerns about transparency and control raised in prior work with professional composers [19]. The qualitative data further illuminated this divide; quotes worrying about plagiarism and the loss of "feeling and life" (P78) exemplify the Skeptic viewpoint, while comments on experimental potential (P34) echo the Enthusiast profile.

A key implication is the near-universal agreement on AGM's potential in education. Even Skeptics see value here, suggesting that educational applications could serve as a "beachhead" for broader acceptance. This separates the perception of AI as a pedagogical aid from its more contentious role as a creative author. This finding resonates with studies like Prassetyo et al. [23], which reported positive views on AGM for creating educational content.

The weak but significant correlation between increasing age and ethical skepticism also warrants discussion. While our study cannot establish causality, it suggests that generational differences in exposure to digital technology and intellectual property paradigms might shape perceptions. This is a crucial area for future research, as the workforce and audience for music continues to evolve.

This study has limitations. Our snowball sampling method may have introduced bias, and the relatively small R-squared value for the age analysis indicates that other unmeasured factors are at play. Future work should employ larger, more diverse samples to validate these profiles. Longitudinal studies could track how perceptions change as AGM technology matures and becomes more integrated into creative workflows. Nonetheless, our findings provide a robust, data-driven framework for understanding the complex and polarized attitudes toward AI-generated music, offering valuable insights for developers, educators, and policymakers navigating this new creative landscape.

6. Ethics Statement

Our research focuses on human opinions, and we do not disclose participants' identifying information. Emails, collected to prevent duplicate responses, were deleted after data collection. Demographic variables are presented only in aggregate. Moreover, given that some participants questioned the relevance of demographic variables such as Race and Gender, we excluded from supplementary materials in respect to these opinions.

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