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AI 음악 창작학습을 위한 SUNO 프롬프트 엔지니어링

Prompt Engineering for AI Music Creation Learning: Application and Analysis Using SUNO AI

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Abstract This study explores the educational potential of prompt engineering in AI-based music creation, focusing on the generative music platform SUNO. By designing prompts based on five variables—genre, instrument, mood, tempo, and technique—I generated and analyzed corresponding 120 audio samples to examine how prompt design affects musical outcomes in school music learning contexts. By using audio feature extraction and quantitative analyses such as similarity matrices, clustering, and dimensionality reduction, I found that detailed and well-structured prompts led to distinct and predictable musical results. In particular, prompts sharing key elements such as instrument or technique produced highly similar audio output, while more varied prompts yielded greater diversity. These findings highlight that prompt engineering can serve as a pedagogical strategy to guide student creativity, support process-oriented learning, and facilitate reflective music inquiry. Based on its finding, this study lays a practical foundation for the educational value of prompt-based AI music creation activities in music education.

Key words: AI music education, prompt engineering, SUNO, music creation, generative music tools

초록 이 연구는 생성형 AI 음악 플랫폼인 SUNO를 중심으로, AI 기반 음악 창작학습에서 프롬프트 엔지니어링의 교육적 가능성을 탐구하였다. 장르, 악기, 분위기, 템포, 구현 방식 등 5가지 변인을 바탕으로 프롬프트를 설계하고, 이에 따라 생성된 120개의 음원을 분석하여 프롬프트 설계가 학교 음악교육 맥락에서 음악적 결과물에 미치는 영향을 살펴보았다. 오디오 특성 추출 및 유사도 행렬, 군집 분석, 차원 축소와 같은 정량적 분석 결과, 세부적이고 구조화된 프롬프트가 보다 명확하고 예측 가능한 음악 결과를 산출하는 것으로 나타났다. 특히 동일한 악기나 구현 방식이 포함된 프롬프트에서는 높은 유사성이, 다양한 조합에서는 음악적 다양성이 뚜렷하게 나타났다. 이러한 결과는 음악적 지식을 통한 지시인 프롬프트 엔지니어링이 학생의 창의성 신장, 과정 중심 학습, 반성적 음악 탐구를 지원하는 교육적 전략이 될 수 있음을 시사한다. 본 연구는 학교 음악 교육 현장에서 프롬프트 기반 AI 음악 창작 활동의 교육적 가치에 대한 실증적 기반을 마련하는 것에 이바지할 것으로 기대한다.

주제어: AI음악교육, 프롬프트 엔지니어링, 수노, 음악창작, 생성형 음악 도구

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Ⅰ. Introduction

1. Purpose of the study

The rapid advancement of artificial intelligence (AI) in recent years has significantly impacted various fields, bringing transformative changes across many sectors of society. Generative AI technology, in particular, has demonstrated remarkable potential within the arts, notably in creative domains such as music. AI-driven music generation platforms democratize the creative process, offering new possibilities for individuals lacking traditional musical training or advanced technical skills (Park & Yang, 2023).

In Korea, recent curricular reforms reflect a growing emphasis on creative music education, marking a shift from traditional teaching approaches focused predominantly on vocal and instrumental performance. The 2022 Revised National Music Curriculum notably introduces "music creation" as a critical area, explicitly emphasizing students' creative expression and active engagement in music-making (D. H. Park, 2024). However, despite these curricular changes, music creation activities remain challenging. Students often encounter substantial barriers due to limited musical knowledge, inadequate technical skills, and apprehensions about creative expression, causing frustration and disengagement (Yang, 2024).

Given these challenges, integrating AI-based tools into music education presents a promising solution. AI-generated music can lower participation barriers by allowing students with minimal theoretical knowledge or instrumental proficiency to engage actively in music creation, thereby minimizing educational disparities and fostering greater inclusion (Kim, 2024). Nevertheless, practical integration of AI-generated music into educational settings remains limited, indicating a clear gap regarding specific guidelines or instructional methods for effective use (Lee & Shin, 2023).

In this context, SUNO AI, a leading generative AI music creation platform, has emerged as a particularly effective and innovative tool. SUNO AI distinguishes itself by its ability to generate fully structured songs—complete with lyrics, vocals, and instrumental accompaniments—based on concise, structured text prompts (Yang, 2024). Unlike other AI music tools, SUNO simplifies the creative process, enabling users to intuitively specify musical styles, emotions, instrumental timbres, and vocal characteristics through simple yet carefully crafted prompts(D. H. Park, 2024). Consequently, SUNO AI is becoming increasingly recognized both academically and practically for its potential to significantly enhance creative efficiency and educational engagement in music creation activities (Park & Yang, 2023).

Despite the potential benefits of SUNO AI, empirical studies investigating the specific impact of prompt engineering—the strategic design of textual prompts for optimal AI-generated outcomes—on students' musical creativity and educational experiences are notably scarce. Prompt engineering involves crafting clear, effective prompts that allow AI systems to accurately interpret and realize musical intentions, significantly influencing the quality and diversity of generated music (Lee & Shin, 2023).

This study addresses these research gaps by examining how SUNO AI-based prompt engineering can be systematically applied in music education, exploring its impact on students' creative experiences and musical outcomes. By doing so, the study seeks to provide concrete instructional guidelines that educators can utilize to effectively integrate AI music creation into classroom activities.

2. Research questions

The specific research questions guiding this study are as follows:

First, How do different prompt engineering strategies using SUNO AI influence the quality and diversity of music created by students?

Second, What patterns and differences emerge in acoustic features and similarity/clustering structures of music generated by varying prompts?

Third, What are the most effective approaches for designing and using SUNO AI prompts to enhance student engagement and creativity in school-based music education?

Therefore, this research aims to facilitate the educational use of AI in music creation, offering practical, systematic guidelines for implementing SUNO-based prompt engineering in music classrooms. By doing so, the study will contribute valuable insights toward the development of more inclusive, creative, and student-centered music education, positioning generative AI as not merely a supplementary technological tool, but as an essential component in cultivating students' musical creativity and expressive skills.

Ⅱ. Literature Review

1. AI-based music creation learning

AI-based music creation learning refers to educational approaches that utilize artificial intelligence technologies to enable or support the process of composing, producing, or analyzing music (Sturm et al., 2019). Unlike traditional methods, where music creation often demands prior knowledge of theory, composition, or instrumental technique, AI lowers entry barriers for students and teachers alike. By providing immediate feedback, scaffolding, and adaptive support, AI tools can help minimize learning gaps and foster more inclusive classrooms (Engel et al., 2019).

A particularly valuable aspect of AI in music education is its role as a "scaffolding" tool, supporting students as they move through their "zone of proximal development" (Chaiklin, 2003; Vygotsky, 1978). With AI assistance, even students with minimal musical background can participate in creative tasks, which might otherwise feel inaccessible. This democratization of the music-making process has significant implications for student motivation, self-efficacy, and creativity (E. B. Park, 2024).

Recently, music educators have begun to advocate for a process-centered, inquiry-based approach to AI music learning, sometimes described as a "paradoxical" or "reverse" model of instruction. In traditional music education, learning typically follows the sequence of theory → context → creation. In contrast, AI-powered classrooms often invert this flow: students begin by generating music with AI, then engage in reflective discussion and analysis, followed by deeper exploration of theory and context inspired by their own creations. This approach, embodying "Learning by Doing," promotes critical thinking, peer dialogue, and active learning, moving beyond surface-level fun to foster lasting musical growth (Dewey, 1933).

2. SUNO AI

SUNO is a cutting-edge AI music generation platform launched in 2023, quickly gaining global attention for its ability to generate complete musical tracks—including lyrics, vocals, and instrumental accompaniments—through simple, structured prompts. Unlike earlier AI music tools, which were often limited to melody or rhythm generation, SUNO produces musically sophisticated outputs that closely resemble commercial music in quality and structure (Yang, 2024).

1) Distinctive features and differences from other AI models

SUNO sets itself apart by allowing users to specify key musical variables—such as genre, instruments, mood, tempo, and vocal style—directly within the prompt. The system then interprets these prompts using large language models and generates music that aligns closely with the user's intent (Liu & Chilton, 2022). This method empowers users to act as creative directors, guiding the AI to realize highly personalized musical ideas without advanced technical skills (E. B. Park, 2024).

2) The logic of SUNO's music generation

SUNO's process typically involves four main stages:

① Prompt interpretation: The AI analyzes the user's text prompt to extract musical parameters.

② Music generation model: Using advanced transformer-based or diffusion models, SUNO translates the interpreted prompt into an audio track.

③ Vocal synthesis: SUNO generates realistic vocals based on input lyrics and the selected vocal style, drawing on technologies like DiffSinger and VQ-VAE for high-quality results (Dhariwal et al., 2020).

④ Post-processing and structuring: The system applies audio engineering techniques—such as mixing, mastering, and arranging sections (intro, verse, chorus, etc.)—to ensure the output sounds polished and musically coherent.

SUNO's transformative power lies in its ability to make professional-level music creation accessible to all learners, regardless of their prior experience. As such, it is gaining traction not only among independent musicians but also as a valuable educational tool in schools (Park & Yang, 2023).

3. Prompt engineering

Prompt engineering is the practice of designing and refining textual instructions (prompts) given to AI systems to optimize the relevance, accuracy, and creativity of their outputs (Liu & Chilton, 2022). In the context of AI music creation, prompt engineering involves thoughtfully selecting keywords or descriptive phrases—such as "jazz, piano, happy, fast tempo, with reverb"—that clearly communicate the user's musical intent to the AI.

The quality and clarity of prompts directly impact the results generated by SUNO and similar systems. If the prompt is too vague, generic, or poorly structured, the resulting music may not reflect the user's intended style, mood, or content. Effective prompt engineering is therefore crucial not only for producing high-quality, meaningful musical works but also for supporting deeper student engagement and learning in creative activities (Yang, 2024).

From an educational standpoint, prompt engineering can also be viewed as a higher-order creative and critical skill. Students must analyze, imagine, and articulate their musical ideas with enough precision for the AI to understand and execute them. In this way, prompt engineering bridges the gap between abstract musical thought and concrete artistic product, making the process itself a form of musical problem-solving and inquiry (Liu & Chilton, 2022).

4. Exploring prompt engineering in AI music creation education

Despite the rapid development of AI music tools and their increasing adoption in schools, empirical research on effective prompt engineering for educational use remains limited (Park & Yang, 2023). Without an understanding of how prompts shape AI-generated music, teachers and students may struggle to fully realize the creative and pedagogical potential of these technologies. Lessons may become shallow, one-off experiences focused only on novelty or entertainment, rather than fostering deeper musical thinking and expression.

Consequently, there is a need for research that systematically examines the impact of prompt design on AI music creation—particularly using platforms like SUNO—within the context of real classroom practice. This study addresses that need by dividing prompts into five key dimensions (genre, instrument, mood, tempo, and technique), generating and analyzing 120 unique musical samples, and exploring how prompt variables affect the quality, diversity, and similarity structure of AI-created music. Through this approach, the research aims to provide clear guidance for teachers on how to design and use prompts effectively, supporting richer and more meaningful music creation learning experiences for all students.

Ⅲ. Method

1. Purpose of the study

The purpose of this study is to analyze the impact of prompt engineering using the AI music generation tool SUNO AI on music creation. The study also aims to identify effective principles and strategies for prompt design that can be practically applied in school music education settings.

2. Research design

The research was structured in three major stages as follows:

1) Prompt design and configuration

Considering the features of SUNO AI, five key musical variables were selected as the basis for prompt design: genre, instrument, mood, tempo, and technique/effect. The representative values for each variable were.

<**Table 1**> SUNO AI Prompt Design

Key musical variables	Prompt
Genre	jazz, ambient, classical, hip-hop
Instrument	piano, guitar, synth, drums
Mood	happy, sad, peaceful, tense
Tempo	slow, medium, fast
Techique/Effect	loop-based, with reverb, 8-bit style

A total of 120 unique prompts were constructed by systematically varying the combinations of these variables. Using these prompts, 120 short musical samples (10 seconds each) were generated with SUNO AI (version 4.5).

2) Data analysis

To understand how similar or different the AI-generated music samples were based on different prompts, it was necessary to carefully analyze each piece of music using a set of specialized computer tools. Instead of just listening and making subjective judgments, this study used a step-by-step process to turn each piece of music into a set of numbers that describe its unique musical features.

First, a software package called librosa was used to “listen” to each music file and extract important musical features. For example, librosa can measure how fast a song is (tempo), how bright or sharp it sounds (spectral centroid), how loud it is (RMS energy), and how rough or smooth the sound is (zero-crossing rate). It also creates a fingerprint of the music's tone called MFCC, which helps describe the overall sound. In simple terms, librosa helps translate what we hear in music into numbers that a computer can analyze.

Next, the pandas and numpy tools were used to organize all of these musical measurements into tables and manage the data efficiently. Pandas is very good at handling large tables of data, while numpy is useful for making calculations with many numbers at once.

To find out how similar or different the 120 music samples were from each other, the study used another tool called scikit-learn. This software can compare the features of any two songs and calculate a "similarity score" between them. If two pieces of music have similar features, their score is high; if they are very different, their score is low. This is known as "cosine similarity," which simply compares how close two sets of musical numbers are pointing in the same direction.

After measuring similarity, the study grouped similar pieces of music together using a method called clustering (specifically, a technique called K-means). This helped show which pieces belonged together based on their musical features. To make it easier to see these groups, the study also used dimensionality reduction techniques like PCA (Principal Component Analysis) and UMAP. These methods take complex data and show it in two or three dimensions, so that patterns and clusters can be seen more clearly on a graph.

Finally, to make the relationships between similar music samples even easier to understand, a tool called networkx was used to create a network graph. In this graph, each music sample is shown as a dot, and lines are drawn between the most similar samples. This way, it is easy to see which pieces of music are most closely related.

By using these tools, the study was able to objectively measure and visualize the unique qualities of each AI-generated song, going far beyond what can be done by listening alone. This approach helps teachers and students better understand how different types of prompts create different musical results and supports the effective use of AI in music education.

The following tools and methods were used to analyze the effectiveness of prompt design:

① Feature extraction:

Audio features were extracted from each sample using Python and the librosa audio analysis library. Extracted features included meta-data and key audio features such as tempo, spectral centroid, zero-crossing rate, RMS energy, and mean MFCCs.

② Similarity matrix analysis:

Cosine similarity matrices were computed based on the extracted audio features to quantitatively evaluate how musical similarity varied according to prompt variables.

③ Clustering and dimensionality reduction:

Hierarchical clustering and K-means clustering were conducted to group samples by similarity. Principal Component Analysis (PCA) and Uniform Manifold Approximation and Projection (UMAP) were used to visualize the high-dimensional feature data in two and three dimensions.

④ Network visualization:

A network graph was constructed to display strong acoustic similarities among samples. Only the top 3% of similarity connections were visualized to highlight meaningful relationships between generated music samples.

3) Research procedure

The research was conducted through the following sequential steps:

Step 1: Prompt construction

120 prompts were created by systematically combining values for each of the five key musical variables.

Step 2: Music generation and data collection

Each prompt was entered into SUNO AI, and 120 ten-second audio samples were generated and systematically archived.

Step 3: Feature extraction and analysis

Various acoustic features were extracted from each sample. These features were used to calculate similarity matrices, perform clustering, and conduct PCA and UMAP dimensionality reduction.

Step 4: Visualization and interpretation

Results from clustering and similarity analysis were visualized through multiple methods. The impact of prompt components on the quality and diversity of generated music was interpreted through these visualizations. Additionally, network analysis was used to identify representative prompt configurations based on strong similarities among samples.

4) Ensuring reliability and validity

To ensure the reliability of the research, all audio samples were processed using identical

Python code and analysis libraries. The entire analysis workflow, including all code and procedures, was carefully documented to enhance objectivity and reproducibility.

The findings of this study are intended to serve as foundational guidelines for designing effective prompts in school music creation classes, providing teachers with concrete strategies to guide students in creative AI-based music activities.

Ⅳ. Results

This chapter presents the quantitative analysis of music data generated by SUNO AI through prompt engineering. The aim is to clarify how different prompt variables affect the quality and similarity of generated music. The results are organized into four main sections: first, descriptive statistics of prompt meta-data and audio features, second, similarity analysis, third, clustering and dimensionality reduction, and fourth, network analysis of music similarity.

1. Descriptive statistics of prompt meta-data and audio features

The 120 music samples analyzed in this study were generated using five main prompt variables: genre, instrument, mood, tempo, and technique. The following table summarizes the main statistics of the extracted audio features, including tempo, spectral centroid, RMS energy, and zero-crossing rate.

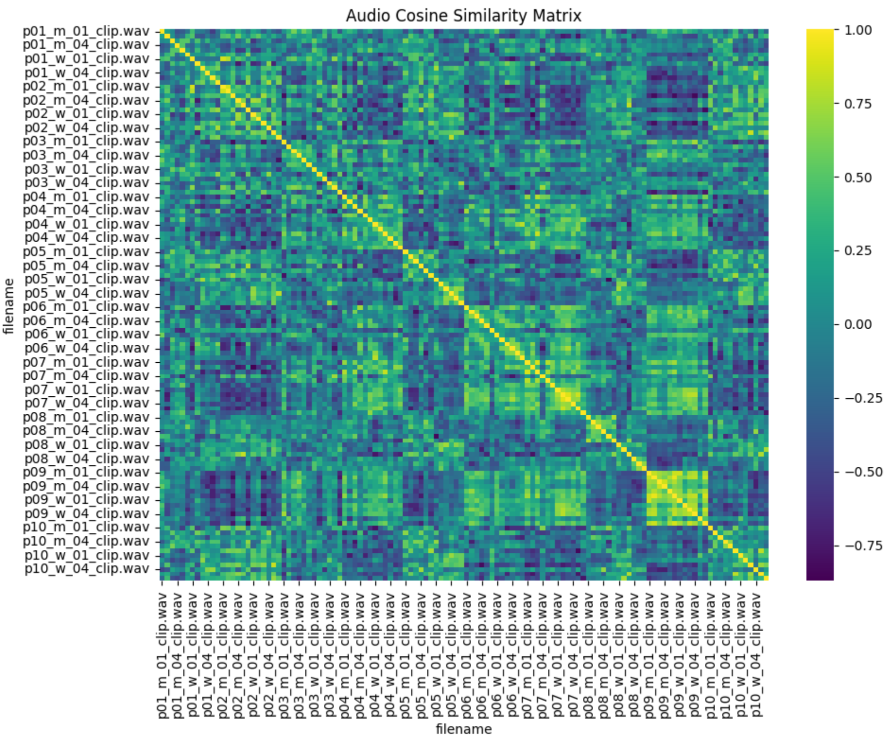
<Table 2> Main statistics of the extracted audio features

Audio feature	Mean	Std. Dev.	Min	Max
Tempo (BPM)	120.4	25.3	68.5	175.3
Spectral centroid	2435.2	562.4	1345.7	3741.8
RMS energy	.06	.02	.03	.12
Zero crossing rate	.09	.03	.03	.17

The analysis shows that audio features differed meaningfully by prompt variables. For example, prompts specifying “fast tempo” resulted in higher average tempo and spectral centroid values. This indicates that prompt engineering has a clear and measurable effect on the generated music’s characteristics.

2. Similarity analysis

Cosine similarity analysis was performed based on audio features such as MFCCs, tempo, and spectral centroid for all 120 music samples generated with SUNO AI.



[Figure 1] Audio cosine similarity matrix

The cosine similarity matrix was visually displayed showing the similarity between each music [Figure 1], which were tagged as ‘prompt_gender_number_clip.wav’. The average similarity was .68 ± .11. The maximum and minimum similarity was .97 and .31, respectively.

First, samples sharing similar prompt elements—especially genre, instrument, mood, and technique—tended to have much higher mutual similarity (often above .7, indicated by brighter matrix colors). This empirically demonstrates that prompt engineering can produce consistent and targeted musical results.

Second, the lower-right section of the matrix (corresponding to Prompt 9, p09) stood out as especially bright, indicating exceptionally high mutual similarity among those samples and lower similarity with samples from other prompts.

Prompt 9 had the following configuration: genre as “rock”, instrument as “electric guitar”, mood as “angry”, tempo as “fast” and technique as “distorted”.

In terms of instrument and technique, the combination of electric guitar and distortion led SUNO AI to generate consistently strong, aggressive sound characteristics (such as heavy distortion and high energy). This made these samples both distinct from other prompts and highly similar to one another.

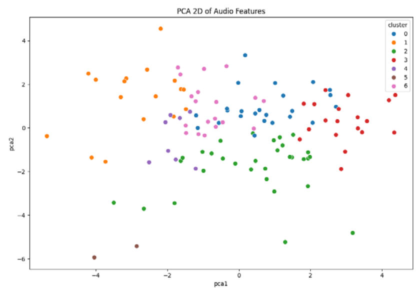
In terms of genre and mood, the “rock” genre combined with an “angry” mood steered the AI to produce driving beats, energetic rhythms, and intense musical textures, further reinforcing sample similarity.

In terms of prompt engineering sensitivity, SUNO AI’s generation model is highly responsive to specific prompt combinations, reliably producing music with clear stylistic and acoustic features. This finding suggests that, in educational settings, teachers can design prompts to achieve particular musical outcomes.

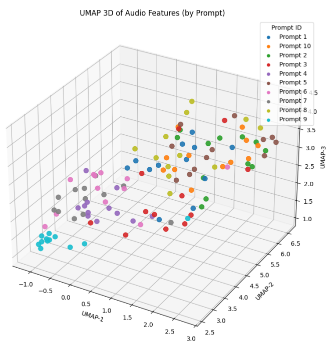
To sum up, prompt configuration—especially the choice of genre, instrument, mood, tempo, and technique—has a strong and direct influence on the acoustic properties of the generated music. The “rock, electric guitar, angry, fast, distorted” combination, in particular, consistently produced tightly clustered results, demonstrating the power of targeted prompt engineering.

3. Clustering and dimensionality reduction

1) PCA (Principal Component Analysis) results



[Figure 2] PCA 2D of audio features



[Figure 3] UMAP 3D of audio features

The audio features [Figure 2] were visualized in two dimensions using PCA. The analysis showed that some prompt variables, such as genre and instrument, were clearly separated— especially “jazz” and “classical” genres.

Variance explained by the first two principal components: 68.7%

This indicates that the chosen audio features effectively represent the musical qualities influenced by prompt engineering.

2) UMAP (Uniform Manifold Approximation and Projection) results

UMAP 3D [Figure 3] was used to project all 120 music samples into a 3D space for better visualization of group patterns by prompt.

Key observations from the UMAP 3D plot:

Prompts formed distinct clusters, with Prompt 9 (rock, electric guitar, angry, fast, distorted) forming a dense and independent cluster—corroborating the similarity analysis.

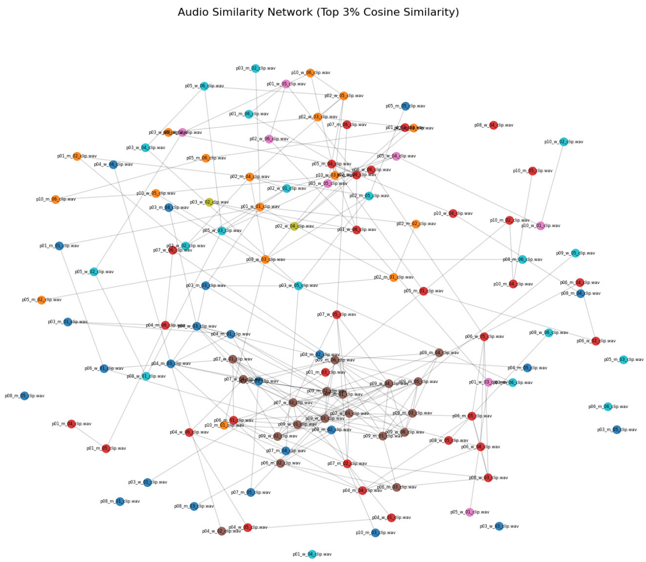
Prompts 5 and 7 showed overlap, suggesting that their respective prompt elements (such as medium tempo and mood or instrument) produced partially similar musical outcomes.

Prompts 1 and 2 were widely dispersed, indicating greater variability and less distinct boundaries. This could result from more diverse or flexible prompt combinations.

Prompts 3, 4, and 8 formed their own relatively independent clusters, with Prompt 8 showing especially distinct characteristics.

The UMAP analysis visually and quantitatively confirms that prompt design can lead to concrete and meaningful differences in the generated music. The configuration of genre, instrument, mood, tempo, and technique in each prompt has a direct and visible effect on musical outcomes.

4. Similarity-based network analysis



[Figure 4] Audio similarity-based network

A network graph was created using only the top 3% of cosine similarity values, visually connecting pairs of music samples with the highest acoustic resemblance.

Network analysis showed that samples with similar prompt variables (especially instrument and technique) formed dense clusters.

For instance, samples featuring “synth” as an instrument were highly interconnected.

5. Summary and discussion

In summary, the prompt variables defined in this study had a strong influence on both the qualitative and quantitative characteristics of the generated music. Instrument, technique, and genre were especially powerful determinants of musical outcome, highlighting the practical value of prompt engineering for creative music tasks.

These results provide practical and empirical criteria for designing prompts in AI-based music learning. In the classroom, teachers can use clear and specific prompts to structure creative exploration and help students achieve targeted learning goals.

In the next chapter, we present concrete educational strategies and guidelines for prompt engineering in school music education, based on these findings.

Ⅴ. Conclusion and Recommendations

This study explored the possibilities of prompt engineering as an effective strategy for integrating generative AI into music composition learning in schools. By focusing on the SUNO AI music generation tool, the study empirically analyzed how prompt design variables influence the qualitative features and similarity of AI-generated music.

The study's main findings can be summarized as follows, each directly addressing the research questions posed in the introduction:

1. Influence of prompt engineering on musical quality and diversity

The results show that prompt engineering has a clear and powerful effect on the characteristics of generated music. Specifically, the variables of genre, instrument, mood, tempo, and technique—all embedded within the prompt—had statistically significant impacts on audio features such as tempo, spectral centroid, and RMS energy. This means that music generated by SUNO AI is not merely the result of random processes. Rather, the musical outcome is shaped in consistent and predictable ways by the chosen prompt elements.

In the context of music education, these results suggest that teachers and students should engage with prompt engineering not simply as a creative exercise, but as a purposeful activity requiring clear musical intentions. The selection of genre terms, instrument choices, and musical vocabulary in the prompt directly affect the music generated by AI. Thus, instead of just "making music with AI," teachers are encouraged to frame composition tasks with specific musical goals or problem-solving contexts. This approach helps students to recognize what kinds of musical knowledge and understanding are necessary to achieve their creative objectives and supports the development of process-oriented, discovery-based, and critical learning.

2. Patterns and differences in acoustic features and similarity

The study's similarity analysis and network analysis further reinforce the importance of prompt design. Music generated from similar prompt combinations—especially those sharing the same instrument or technique—tended to show high levels of acoustic similarity. For example, prompts specifying "electric guitar" and "distorted" in a rock context consistently produced highly similar and distinct musical results. Clustering analyses using PCA and UMAP demonstrated that prompts led to clear groupings in the feature space, confirming that prompt variables strongly structure the diversity and organization of AI-generated music.

These findings demonstrate that prompt-based music generation can deliver consistent, intentional creative outcomes, rather than unpredictable or arbitrary results. They also provide evidence that prompt engineering can be used as a practical strategy for achieving educational objectives in music creation.

3. Recommendations for classroom practice

Based on these findings, several practical recommendations can be made for the effective use of SUNO AI and prompt engineering in school music education:

Clarity in Prompt Design: Teachers should introduce composition tasks with clear and specific prompt elements—such as genre, instrument, mood, tempo, and technique—to guide students toward intentional and goal-oriented creative experiences. This not only reduces uncertainty and anxiety but also increases student motivation and engagement in music-making.

Reflective Analysis: Students should be encouraged to engage in reflective analysis of the music they generate. Asking critical questions about the relationship between their prompt choices and the resulting musical features helps deepen musical understanding and expressive ability.

Data-Informed Feedback: Schools are encouraged to adopt data-driven approaches (such as similarity analysis of student work) to provide objective and systematic feedback on student compositions. Such feedback systems can help students better understand and improve their creative processes.

4. Limitations and future directions

This study still holds important music educational implications. The educational potential discussed here lies primarily in the finding that AI-generated music is not randomly or arbitrarily produced by the AI's programming alone, but is instead significantly influenced by specific user-defined prompts. Demonstrating that musical outcomes can be predictably controlled through intentional prompts provides crucial groundwork for future music educational applications.

Last but not least, if AI-generated music can be clearly and systematically changed by prompts of learners' intentions—such as musical elements like rhythm, melody, harmony, tempo, dynamics, form, and timbre, all expressed through prompts—then AI tools could become truly practical resources for music education. Helping students develop the ability to create accurate musical prompts would tightly connect their musical knowledge with digital literacy. This would also set a valuable direction for future research, such as designing new teaching models, developing music programs, and music educations.

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