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Research Article ♪ **Araştırma Makalesi**

An analysis of influencing factors of generative AI in pop music creation

Pop müzik yaratımında üretken yapay zekanın etki eden faktörlerinin analizi

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ABSTRACT

The fast pace of generative artificial intelligence (AI) has already revolutionized several creative fields, especially pop music production, by introducing fresh composition, production, and sound design tools. This research explores the determinants of generative AI adoption within pop music production based on Partial Least Squares Structural Equation Modeling (PLS-SEM) to examine its influence on creativity, production practices, and industry sentiment. The investigation hypothesizes that generative AI improves creative production by changing music creation procedures and influencing listener commitment. The investigation examines several important factors, such as user engagement (UE), artist autonomy (AA), collaborative perception (CP), emotional effect (EI), perceived quality of AI-generated music (PQ), creativity enhancement (CE), and music production efficiency (MPE). A total of 100 professional composers and 200 aspiring artists along with 500 music listeners formed the sample that completed surveys and collaborated with AI in music creation activities. SmartPLS 3.2.9 performed statistical testing using path analysis techniques, which examined direct and indirect variable relationships through structural equation modeling procedures. The results indicate that CE ($\beta = 0.298$, $p < 0.01$) and UE ($\beta = 0.248$, $p < 0.05$) have a significant impact on the adoption of AI tools in music production, while PQ plays a substantial role in determining both behavioral intention (BI) and actual usage behavior (UB). The findings propose that while AI tools are widely included by fresher artists for their creative latent, concerns regarding authorship rights, originality, and the role of human participation in music-making remain. This exploration contributes to a deeper empathy of how AI is reshaping pop music creation and offers valuable insights into its broader implications for the music industry.

Keywords: generative AI, pop music creation, creativity enhancement, music production efficiency, user engagement, music composers

ÖZ

Üretken yapay zekanın (YZ) hızlı temposu, özellikle pop müzik prodüksiyonu olmak üzere birçok yaratıcı alanda, yeni kompozisyon, prodüksiyon ve ses tasarımı araçları sunarak devrim yarattı. Bu araştırma, yaratıcılık, prodüksiyon uygulamaları ve endüstri duygusu üzerindeki etkisini incelemek için Kısmi En Küçük Kareler Yapısal Eşitlik Modellemesine (PLS-SEM) dayalı olarak pop müzik prodüksiyonunda üretken yapay zeka benimsenmesinin belirleyicilerini araştırıyor. Araştırma, üretken yapay zekanın müzik yaratma prosedürlerini değiştirerek ve dinleyici bağlılığını etkileyerek yaratıcı prodüksiyonu iyileştirdiğini varsayıyor. Araştırma, kullanıcı katılımı (UE), sanatçı özerkliği (AA), işbirlikçi algı (CP), duygusal etki (EI), yapay zeka tarafından üretilen müziğin algılanan kalitesi (PQ), yaratıcılık geliştirme (CE) ve müzik prodüksiyon verimliliği (MPE) gibi birkaç önemli faktörü inceliyor. Toplamda 100 profesyonel besteci ve 200 hevesli sanatçı ile birlikte 500 müzik dinleyicisi, anketleri tamamlayan ve müzik yaratma faaliyetlerinde YZ ile iş birliği yapan örneği oluşturdu. SmartPLS 3.2.9, yapısal eşitlik modelleme prosedürleri aracılığıyla doğrudan ve dolaylı değişken ilişkilerini inceleyen yol analizi tekniklerini

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kullanarak istatistiksel testler gerçekleştirdi. Sonuçlar, CE'nin (β = 0,298, p < 0,01) ve UE'nin (β = 0,248, p < 0,05) müzik prodüksiyonunda AI araçlarının benimsenmesinde önemli bir etkiye sahip olduğunu, PQ'nun ise hem davranışsal niyeti (BI) hem de gerçek kullanım davranışını (UB) belirlemede önemli bir rol oynadığını göstermektedir. Bulgular, AI araçlarının yaratıcı gizli nitelikleri nedeniyle daha yeni sanatçılar tarafından yaygın olarak dahil edilmesine rağmen, yazarlık hakları, özgünlük ve müzik yapımında insan katılımının rolüyle ilgili endişelerin devam ettiğini öne sürmektedir. Bu araştırma, AI'nın pop müzik yaratımını nasıl yeniden şekillendirdiğine dair daha derin bir empatiye katkıda bulunmakta ve müzik endüstrisi için daha geniş etkilerine dair değerli içgörüler sunmaktadır.

Anahtar kelimeler: üretken AI, pop müzik yaratımı, yaratıcılığın artırılması, müzik prodüksiyon verimliliği, kullanıcı katılımı, müzik bestecileri

1. INTRODUCTION

The advent of AI brought model changes in everything, and the field of music is not an exception. More and more AI has been utilized in music composition in recent decades, and it can transform the field of music composition, music production, and music listening (Li, 2025). This trend is highest in the pop music industry, where innovation and trends are key drivers of success. Artificial intelligence-based software is empowering artists, producers, and songwriters to enhance the reach of creativity and streamline their workflow, with both potential and issues (Ojukwu, 2024). AI music generator systems operate through intricate computing methods combined with machine learning applications to explore extensive information databases that contain both song fundamental structures and chord sequences and rhythm designs alongside musical word content. AI conducts pattern analysis that enables it to produce new music that mimics different musical genres and individual artists (Ferreira et al., 2023). The music programs of OpenAI's MuseNet together with Jukedeck enable users to generate polished music through minimal human interaction, which produces distinctive musical segments that mimic professional production standards. New technological advances have transformed musical creativity because they dissolve traditional musical creation limitations (Cipta et al., 2024).

Pop music is the genre in which AI supremacy is the most prevalent. Pop music has hooks, repetitive structure, and popularity on a gargantuan scale, and pop is the ideal genre for AI music. Its ability to produce new music fairly quickly and in massive amounts has created a deluge of AI-generated music, some even becoming commercially successful (Zhang et al., 2023). This has led the industry to wonder if AI music is authentic and what it does to the role of human creativity in music. For some, they view AI as watered-down, a subjective expression that is in music, whereas for others, AI is a tool that carries the art of possibility forward, providing new material for artists to use (Tan, 2024). This convergence of AI and pop music also has implications for the future of the music industry, specifically regarding issues such as copyright, the music production economy, and how artists are related to machines (Sturm et al., 2019). With AI continuing to evolve, its impact on pop music can only grow, transforming the music industry in ways that are currently only starting to be realized. Eventually, the job that AI will do for music composition will set the future world of sound and imagination for music (Alaeddine & Tannoury, 2021).

The greatest challenges to implementing generative AI in pop music production are control over art, originality, and emotional value in AI-produced music. Copyright, authorship, and reception issues also make it difficult. The objective of this investigation is to explore the elements that impact the use of generative AI to produce pop music, with an emphasis on how it affects industry perceptions, production efficiency, and originality. The examination uses PLS-SEM analysis to examine important factors influencing AI adoption and offers insights into how it might revolutionize music creation, artist cooperation, and audience engagement.

This research explores prior research in part 2, employs robust methodologies in part 3, presents significant findings in part 4, interprets them critically in part 5, and concludes with key insights, highlighting contributions and potential implications for future research and applications in part 6.

2. RELATED ARTICLES

The utilization of generative AI in music and art, emphasizing methods including Generative Adversarial Networks–recurrent neural networks (GAN- RNN) that motivate creativity investigation, was examined (Jaini & Katikireddi, 2022). It provided case studies and examined cutting-edge models. The effects on music production and industry reaction to AI-generated fan material that imitates the voices of retiring or deceased musicians were analyzed (Galuszka, 2024). It examined three representative works: one parody and two fan-driven pieces. The use of generative AI in music creation and its implications for the future of the sector were examined (Novikova, 2024). A survey of the literature was used to develop a theoretical framework, and content analysis of online forum conversations was used to carry out qualitative research. An AI-powered application called LyricJam Sonic was presented in the experiment (Vechtomova & Sahu, 2023) to assist electronic artists in re-discovering and contextualizing old recordings for live music production. To discover appropriate audio snippets and produce a continuous music stream, a bi-modal AI system created lyric lines.

The application of GANs in music and art production was examined (Atlas et al., 2025), with a focus on creative autonomy and human-AI co-creation. AI-generated outputs might be guided by artists using a hybrid model with feedback loops, guaranteeing that it was in line with human aesthetics. The investigation (Bryce, 2024) examined AI-generated music with an emphasis on ethical issues, emotional resonance, and technological procedures. 46 students blindly assess AI and human tracks in two trials, with a presentation in between, while a Music Variational Autoencoder creates music. The focus of the investigation (Deruty et al., 2022) was studio-based genres and creative workflows, as it examined AI music technologies in modern popular music. It reflected on professional artist collaborations, looked at production methods, and compared AI technologies that were based on symbols and sounds. Deep generative AI-based video-to-music synthesis was examined, classifying important elements and techniques (Ji et al., 2025). Along with datasets and assessment measures, it looks into visual feature extraction, music creation frameworks, and conditioning methods. Table 1 illustrates the related articles' results and limitations.

Table 1

Overview of Literature Review

Ref	Year	Result	Limitation
Jaini and Katikireddi, 2022	2024	AI is capable of producing original music and artwork; it confronts ethical and creative process issues	It's unclear how to balance AI's function as a tool and a programmable creator.
Galuszka, 2024	2024	AI covers combine industry control, inventiveness, and homage.	There were unsolved ethical issues and industry restrictions.
Novikova, 2024	2024	Users pointed out the advantages of AI in music production	However, it also highlighted the drawbacks like results are restricted to arbitrary internet debates.
Vechtomova and Sahu, 2023	2023	By decreasing the amount of manual searching, the tool improves creative flow.	Artificial intelligence might reduce creative freedom and spontaneity.
Atlas et al., 2025	2025	Collaboration between humans and AI fosters creativity; 89% of respondents found music to be satisfying, and 85% found AI art to be inspirational.	Authorship, originality, and preserving creative authenticity continue to be difficult.
Bryce, 2024	2024	Education increased discernment and music experience helps AI detection.	The scope of the genre and sample size restricts the findings.
Deruty et al., 2022	2022	Although it improved creativity, AI programs might be difficult to use.	Integration, validation, and optimization for practical manufacturing remain challenges.
Ji et al., 2025	2025	It identifies key modality types and explains design techniques.	There were still issues with model robustness, assessment consistency, and dataset availability.

2.1. Hypothesis development

The quantitative approach using PLS-SEM tests the hypotheses developed for the drivers of generative AI in pop music creation.

H1: CE positively influences BI to make use of AI in music production. CE → BI
H2: The PQ of AI music has a beneficial impact on BI's use of AI tools. PQ →BI
H3: PQ significantly influences the actual UB of AI in music creation. PQ→UB
H4: AA has a positive influence on BI to utilize AI in music composition. AA→ BI
H5: CP has a positive effect on CE when using AI tools. CP →CE→BI
H6: The EI of AI music positively influences UE. EI→UE → BI
H7: UE plays an important role in BI's utilization of AI in music composition. UE →BI
H8: MPE positively impacts the real UB of AI for music production. MPE →UB
H9: BI has a positive effect on the actual UB of AI tools in creating music. BI→ UB

Figure 1

Conceptual diagram

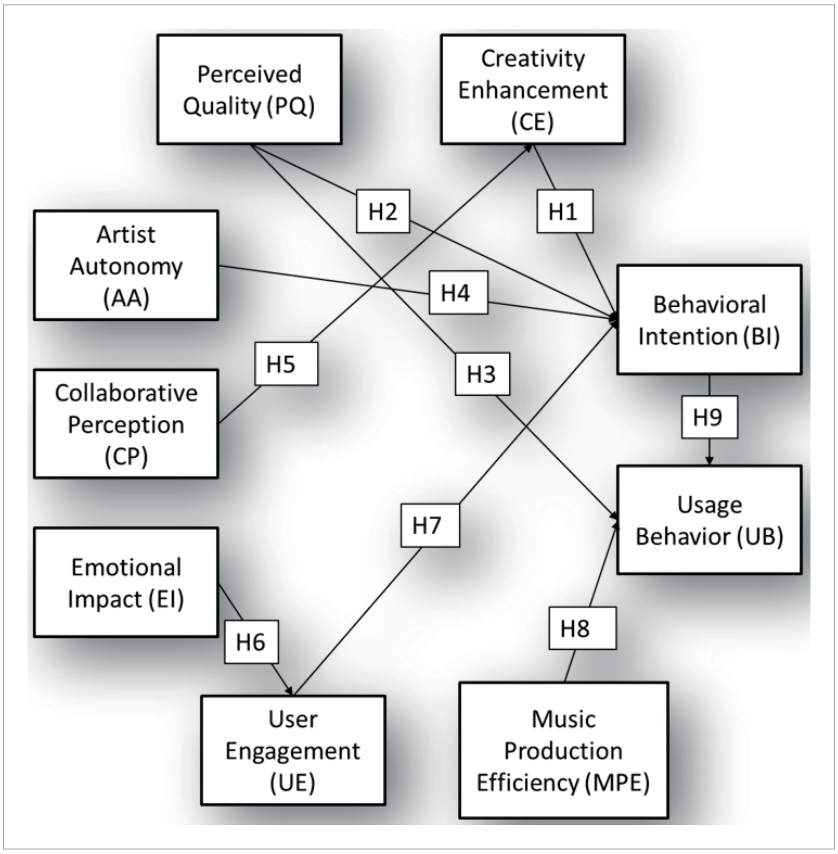


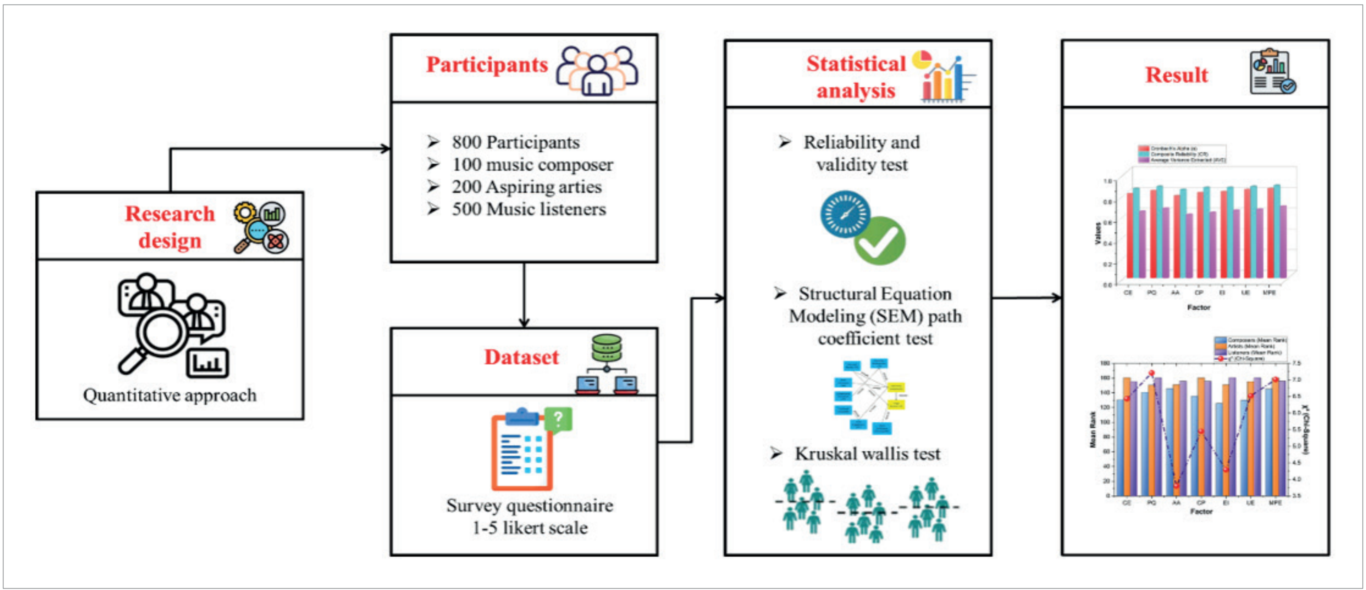
Figure 1 depicts the conceptual structure and demonstrates how various factors impact AI adoption in pop music production. Creativity enhancement (CE), perceived quality (PQ), and artist autonomy (AA) are directly affecting behavioral intention (BI) to employ AI tools. Collaboration perception (CP) boosts CE, besides emotional impact (EI) increasing user engagement (UE), which in turn affects behavioral intention (BI). Moreover, perceived quality (PQ) and music production efficiency (MPE) both have direct influences on actual usage behavior (UB). Finally, BI has a strong influence on the actual UB of AI for music production. The model allows to see how the adoption of AI for music is influenced by production efficiency, engagement, and creativity.

3. METHODOLOGY

The exploration utilizes a quantitative approach with Partial Least Squares Structural Equation Modeling (PLS-SEM) to examine drivers of generative AI adoption in pop music production. A cross-sectional survey was administered to 100 composers, 200 emerging artists, and 500 listeners. The relationships between CE, PQ, AA, and other important variables are examined. Figure 2 illustrates the proposed basic concept.

Figure 2

Fundamental concept of suggested research



3.1. Participants

The survey had 800 participants, including 100 composers, 200 aspiring artists, and 500 music listeners. Composers and artists discussed AI's influence on creativity and production, while listeners evaluated AI-generated music. This varied group made certain that everyone had a full understanding of how AI affects music production, perception, and industry acceptance from a variety of perspectives. Table 2 shows the participant's profile details. Males were the majority, especially among composers (60%) and artists (55%). Most participants were 18-35 years old, with listeners skewing younger. Experience levels varied, with composers being more advanced, while most listeners were beginners. Interest in generative AI was highest among composers (70%) and artists (65%), while 40% of listeners showed moderate interest. This diverse sample provided insights into AI's impact on creativity, production, and audience perception in pop music.

Table 2

Demography Data for Participants

Category	Music Composers (N=100)	Aspiring Artists (N=200)	Music Listeners (N=500)
		Gender	
Male	60 (60%)	110 (55%)	250 (50%)
Female	40 (40%)	90 (45%)	250 (50%)
		Age	
18-25 years	20 (20%)	80 (40%)	300 (60%)
26-35 years	50 (50%)	70 (35%)	120 (24%)
36-45 years	20 (20%)	30 (15%)	50 (10%)
46+ years	10 (10%)	20 (10%)	30 (6%)

Experience Level			
Beginner	10 (10%)	100 (50%)	400 (80%)
Intermediate	50 (50%)	70 (35%)	80 (16%)
Advanced	40 (40%)	30 (15%)	20 (4%)
Interest in Generative AI			
High Interest	70 (70%)	130 (65%)	200 (40%)
Moderate Interest	20 (20%)	50 (25%)	200 (40%)
Low Interest	10 (10%)	20 (10%)	100 (20%)

3.1.1. Inclusion Criteria

The inclusion criteria include music composers, potential musicians, and music consumers engaged or interested in music production and consumption; people aged 18 years and older have to give legal consent to participate; participants with general to professional knowledge of AI in music (for musicians and composers); voluntariness in filling out surveys and participating in AI-assisted music-making tasks; and experienced listeners who evaluate or interact with music created through AI.

3.1.2. Exclusion Criteria

The exclusion criteria include people under the age of 18 for moral reasons; people not exposed to or interested in AI music generation; experienced composers or producers who have never employed AI software for music production; sound listeners without prior experience in criticizing music generated with AI; and incomplete criticism or refusal to participate in mandatory analysis on the focus.

3.2. Data collection

The data was obtained based on the sample of 1,000 questionnaires circulated among respondents, 800 of which had returned valid and full responses and 200 others left incomplete or empty responses. The questionnaire tool utilized a Likert scale with five points: 1 for strongly disagreeing and 5 for strongly agreeing in capturing the attitude of the participants regarding AI usage in pop music creation. The right answers provided data concerning key factors that CE, PQ, AA, CP, EI, UE, MPE, BI and UB of the evaluation.

1. CE-How does AI help you generate new musical ideas and inspirations?
2. PQ-Do you think AI-generated music sounds professional and high-quality?
3. AA- Does AI allow you to maintain artistic control over your compositions?
4. CP- Do you see AI as a creative partner rather than a replacement for human creativity?
5. EI-Can AI-generated music evokes emotions similar to human-composed songs?
6. UE- Does AI-generated music attract strong audience engagement?
7. MPE- How does AI speed up your music production process?
8. BI- Are you willing to continue using AI tools for music composition?
9. UB- How frequently do you use AI tools in your music composition process?

3.3. Statistical analysis

The research employs PLS-SEM through SmartPLS 3.2.9 for statistical testing. It includes the reliability and validity test for verifying measurement accuracy, SEM tests for testing relationships, and the Kruskal-Wallis test for testing the difference between several groups' perceptions of AI use in music production.

4. EXPERIMENTAL ANALYSIS RESULT

This section emphasis is on how various factors impact the application of generative AI in pop music production. The findings are mostly derived from PLS-SEM analysis, investigating the direct and indirect effects of influential variables.

4.1. Reliability and validity test

Reliability is the endurance or consistency of a measuring instrument over time. It tells us if a test result can be repeated under the same conditions. Validity is the precision of a measuring instrument, determining if the test is measuring what it is supposed to, and to what degree the result represents the intended construct or variable. Table 3 shows the factor load and reliability tests. The factor load exceeds the criterion of 0.6 (Cronbach's alpha - α). The Composite Reliability (CR) and Average Variance Extracted (AVE) values were more than 0.7, meeting statistical reliability standards. Reliability is also generally computed using Cronbach's Alpha (α) to determine internal consistency was shown in equation (1).

$$\alpha = \frac{l}{l-1}\, 1 - \frac{\sigma_j^2}{\sigma_s^2} \quad (1)$$

Here I is the integer of items, $\sigma_j{}^2$ denotes the variation of each distinctive item and the overall variation of all components combined.

Table 3

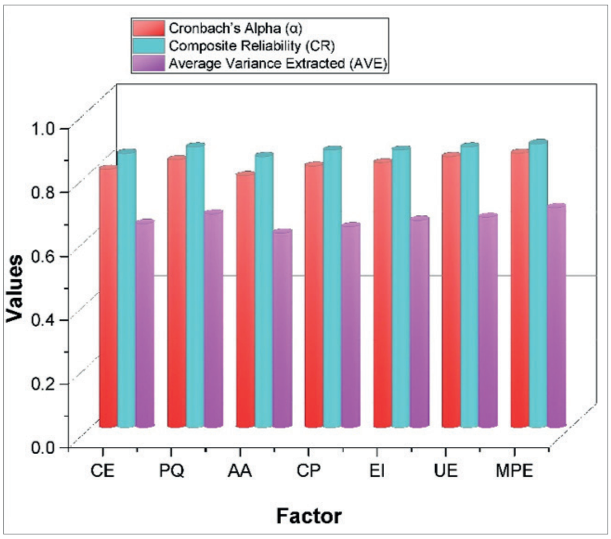
Reliability and validity test result

Construct	Factor Loadings	Reliability Coefficient	CR	AVE	α
CE	0.75	0.78	0.86	0.64	0.81
PQ	0.81	0.82	0.88	0.67	0.84
AA	0.72	0.76	0.85	0.61	0.79
CP	0.73	0.79	0.87	0.63	0.82
EI	0.76	0.8	0.87	0.65	0.83
UE	0.75	0.81	0.88	0.66	0.85
MPE	0.86	0.83	0.89	0.69	0.86

Note: BI and UB are dependent variables.

Figure 3

α, CR, and AVE for each construct of Reliability and validity test



The validity and reliability analysis in Table 3 shows the results for the measurement properties of each construct. Factor loadings are all greater than 0.70, which shows high correlations with the constructs. The reliability coefficient values show internal consistency and CR values are greater than 0.80, which verifies the reliability of the constructs. AVE values greater than 0.50 show that each construct explains adequate variance. α is greater than 0.70, which establishes the reliability of the scale for all constructs as shown in Figure 3. The findings show that the measurement model is valid and reliable.

4.2. SEM path analysis

To evaluate the connections between variables and the overall model's fit to the data, a typical SEM results table displays important findings, such as path coefficients, their significance (p-values), and model fit indices. These show how strongly and in which direction the variables are related to other variables. SEM analyzes associations between latent variables via path coefficients (β), which follow equation (2).

$$Z = \beta W + \varepsilon \qquad (2)$$

Z refers to the dependent variable, *W* denotes the independent variable, and *β* represents the path coefficient (relationship strength). ϵ stands for "error term."

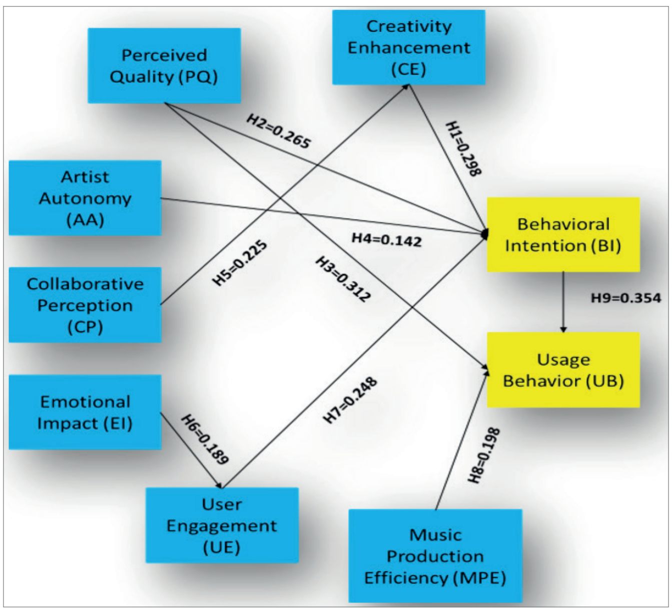
Table 4

SEM path analysis of various hypothesis relationship factors

Hypothesis	Path	Coefficient (β)	t-Values	p-Values	Decision
H1	CE → BI	0.298	4.21	<0.01	Supported
H2	PQ → BI	0.265	3.89	<0.01	Supported
H3	PQ → UB	0.312	5.02	<0.01	Supported
H4	AA → BI	0.142	2.37	0.018	Supported
H5	CP → CE → BI	0.225	3.45	<0.01	Supported
H6	EI → UE → BI	0.189	2.91	0.004	Supported
H7	UE → BI	0.248	3.68	<0.05	Supported
H8	MPE → UB	0.198	2.74	0.006	Supported
H9	BI → UB	0.354	6.12	<0.01	Supported

Figure 4

Path coefficient diagram



The SEM evaluation validates that all of the nine hypotheses are highly supported, showing robust correlations between generative AI uptake and influence factors as shown in Figure 4 and Table 4. CE ($\beta = 0.298$, $p < 0.01$) and UE ($\beta = 0.248$, $p < 0.05$) both have a very strong effect on BI to employ AI in music. PQ ($\beta = 0.312$, $p < 0.01$) is the most influential determinant of BI and UB. Also, MPE and EI influence AI adoption indirectly. The overall result is that although AI maximizes creativity and engagement, the issues of originality and authorship persist in determining its role in pop music production in the future.

4.3. Kruskal-Wallis test

A non-parametric statistical test for comparing the medians of two or more independent groups, the Kruskal-Wallis test (sometimes called one-way ANOVA on ranks) is especially useful when the data doesn't follow a normal distribution.

Table 5

Outcome of the Kruskal-Wallis test

Factor	Group	Sample Size	Mean Rank	χ^2 (Chi Square)	df	p-Value
CE	Composers	100	130.5	6.43	2	0.04
	Artists	200	160.4			
	Listeners	500	155.2			
PQ	Composers	100	140.6	7.21	2	0.027
	Artists	200	150.3			
	Listeners	500	160.1			
AA	Composers	100	145.8	3.8	2	0.15
	Artists	200	150.9			
	Listeners	500	155.7			
CP	Composers	100	135.3	5.45	2	0.066
	Artists	200	160.2			
	Listeners	500	155.6			
EI	Composers	100	125.4	4.29	2	0.116
	Artists	200	150.8			
	Listeners	500	160.3			
UE	Composers	100	130	6.52	2	0.039
	Artists	200	155.1			
	Listeners	500	160.2			
MPE	Composers	100	145.2	7.01	2	0.03
	Artists	200	160.5			
	Listeners	500	155.9			

Figure 5

Mean Rank and Chi-Square (χ^2) Values for Factors Influencing Generative AI in Pop Music Creation

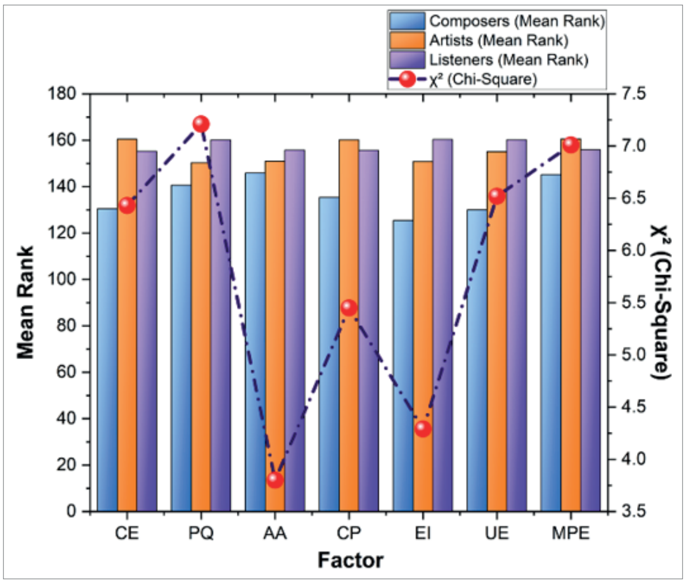


Figure 5 shows the mean rank distributions for important AI-generated music-related parameters for the three participant groups (listeners, artists, and composers). The Kruskal-Wallis test outcomes in Table 5 show statistically significant differences in the perception of generative AI among composers, artists, and listeners concerning CE ($p = 0.040$), PQ ($p = 0.027$), UE ($p = 0.039$), and MPE ($p = 0.030$). This shows that the factors affect the use of AI differently across groups. However, differences were not found for AA, CP, and EI, indicating a more balanced perception among participants. These results indicate important areas where AI adoption differs, influencing its role in pop music production.

5. DISCUSSION

Generative AI is revolutionizing pop music production with automated composition, accelerated creativity, and a new definition of artistic collaboration. The analysis discusses the principal drivers of its application, influence, and prospects in the music industry. The outcomes from the research validate that generative AI plays a substantial role in pop music creation throughout CE and UE. The constructed measurements demonstrate robust measurement properties through three reliability and validity tests where $\alpha > 0.70$ and CR> 0.80 as well as AVE >0.50. The SEM results show that PQ ($\beta = 0.312, p < 0.01$) has the greatest impact on UB and BI, whereas CE ($\beta = 0.298, p < 0.01$) and UE ($\beta = 0.248, p < 0.05$) have a significant impact on BI. The Kruskal-Wallis test shows there were significant differences in CE ($p = 0.040$), PQ ($p = 0.027$), UE ($p = 0.039$), and MPE ($p = 0.030$) between groups, reflecting diverse perceptions of AI adoption. AA, CP, and EI are not significantly different, reflecting homogeneous perceptions of these elements. These findings show the potential of AI but also reflect creativity and authorship issues in music composition.

6. CONCLUSION

The variables that influence the use of generative AI in pop music production through an assessment of creative effects and manufacturing practices alongside industry acceptance were evaluated. The investigation adopted a quantitative method along with PLS-SEM for analyzing major variables. A total of 100 music composers, 200 aspiring artists, and 500 music listeners completed surveys and experienced AI-assisted music production tasks. Measurement reliability and validity tests confirmed that the constructs met the reliability criteria. The SEM tests measured the relationships between CE, PQ, and UE in addition to other variables that significantly influenced BI and UB. Groups displayed distinct AI perception patterns according to the results from the Kruskal-Wallis test. The analysis data revealed both CE with a $\beta = 0.298, p < 0.01$, and UE with $\beta = 0.248, p < 0.05$ as significant influencing factors for AI adoption. Concerns concerning musical originality and authorship validity continue to impede AI's musical progress, despite constant technical advancements.

Limitation and future scope

Limitations of pop music composition using generative AI include ethical issues, originality issues, and reliance on high-quality training data. Moreover, AI music cannot be anticipated to be emotionally rich or intuitive like human music. Future directions for improvement are to make AI models more creative, develop better ethical policies, and blur AI with human composers to produce more creative and emotional music.

Ethical approval

This study does not require ethics committee approval as it does not involve human, animal or sensitive data.

Author contribution

Study conception and design: SZ, HK; data collection: SZ, HK; analysis and interpretation of results: SZ, HK; draft manuscript preparation: SZ, HK. All authors reviewed the results and approved the final version of the article.

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Conflict of interest

The authors declare that there is no conflict of interest.

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