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Generative AI Driven Cultural Content Production Mechanisms and Creative Labor Substitution Effects

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Abstract. Generative AI is reshaping content production in the cultural and creative industries by shifting cultural material organization, script writing, exhibition interpretation, and cultural tourism communication from linear manual workflows to human-AI collaborative workflows. Focusing on productivity improvement and the boundary of creative labor substitution, this research constructs a three-group comparison framework involving human-only creation, AI-assisted creation, and fully AI-generated creation. Based on public cultural heritage data, cultural policy texts, and cultural tourism communication samples from 2018 to 2024, LLMs, RAG, Sentence-BERT semantic retrieval, expert scoring, and mixed-effects ANOVA are combined to measure generation quality, policy suitability, and substitution intensity across different cultural tasks. The results show that the average completion time of the AI-assisted group decreases from 44.2 min to 25.7 min, while the overall quality score increases from 82.6 to 84.1, indicating that human-AI collaboration can improve production efficiency while maintaining content quality. Although the fully AI-generated group achieves the lowest time cost, its policy suitability and cultural accuracy decline noticeably. Task complexity further affects substitution intensity. Cultural tourism copy and short-video scripts are more substitutable, while exhibition interpretation and policy explanation still rely on human judgment. These findings provide quantitative evidence for AI adoption, creative labor restructuring, and cultural policy governance.

Keywords: Generative AI, Cultural Content Production, Creative Industries, Creative Labor, Cultural Policy

1. Introduction

The cultural and creative industries are shifting from experience-based manual production to an intelligent production model that integrates data, algorithms, and creative collaboration. Generative AI has been applied to cultural material organization, copywriting, short-video scripting, exhibition interpretation, and cultural tourism communication. Existing studies show that generative AI can significantly reduce the completion time of writing and knowledge-intensive tasks while improving first-draft generation and idea expansion efficiency [1]. In real work settings, AI tools also change task allocation by absorbing basic content production, material restructuring, and standardized expression into algorithmic systems [2]. Cultural content production involves historical context,

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symbolic interpretation, aesthetic judgment, and public value orientation, so evaluating AI only through efficiency may overlook cultural accuracy, policy suitability, and changes in creative labor structure [3]. By comparing human-only creation, AI-assisted creation, and fully AI-generated creation, public cultural data, RAG-based generation, semantic evaluation, expert scoring, and statistical testing can be combined to examine AI-driven cultural content production mechanisms, quality boundaries, and creative labor substitution paths.

2. Literature review

2.1. Generative AI content production

Research on generative AI content production emphasizes the role of large language models and multimodal models in supporting cultural material organization, topic generation, narrative expansion, and stylistic transformation. Related studies indicate that generative AI can integrate prompt design, semantic generation, and iterative rewriting into a continuous process, giving cultural text production higher speed and stronger scalability [4]. In museum exhibitions, intangible cultural heritage communication, urban cultural tourism, and policy explanation, generated texts need to be fluent while maintaining stability in facts, context, and value expression. Creative industry research further shows that AI can increase the number of content alternatives and improve production efficiency, while the meaning construction of cultural content still depends on human verification, aesthetic selection, and communication strategy control [5]. Therefore, RAG and semantic retrieval can connect model outputs with public cultural heritage materials, policy texts, and cultural tourism resources, shifting generation from open-ended production to culturally grounded content production.

2.2. Creative labor substitution boundary

Research on creative labor substitution focuses on how AI restructures job tasks rather than simply judging whether human labor is entirely replaced. Cultural economy research argues that creative products involve uncertainty, dependence on differentiated talent, and complex collaborative relations, making their production process different from standardized industrial production [6]. Under generative AI conditions, headline generation, cultural tourism copywriting, first drafts of short-video scripts, and basic material rewriting are more likely to be substituted because these tasks have clear formats, stable semantic goals, and lower cultural interpretation risks. Research on cultural labor further points out that after AI intervention, human roles may shift from direct writing to prompt design, content selection, fact-checking, and value judgment [7]. Therefore, the substitution boundary needs to be identified through task complexity, cultural term density, policy constraint quantity, and expert quality scores, so that the practical differences among AI assistance, human-AI collaboration, and full automation can be explained.

2.3. Cultural policy governance evidence

From a cultural policy perspective, generative AI application must respond to industrial efficiency, copyright responsibility, labor rights, and cultural diversity at the same time. Research on AI application in cultural and creative sectors indicates that AI can promote content production innovation while also creating governance issues related to authorship, data transparency, and responsibility attribution [8]. When cultural institutions use AI for public communication, content

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generation speed and communication frequency may increase, while cultural errors, unclear sources, and value bias may also spread through formal communication channels. AI governance research emphasizes that once algorithmic systems are embedded in social and cultural decision-making environments, transparent evaluation mechanisms and clear institutional responsibility are required [9]. Therefore, by comparing human-only, AI-assisted, and fully AI-generated outputs in time cost, cultural accuracy, originality, attractiveness, and policy suitability, empirical evidence can be provided for AI-use boundaries, human review procedures, data-source labeling, and creative labor retraining.

3. Experimental methods

3.1. Public data sources

Data collection focuses on three types of materials: cultural heritage content, cultural policy texts, and cultural tourism communication samples. The time span is set from 2018 to 2024. Cultural heritage materials are collected from UNESCO Intangible Cultural Heritage Lists, Europeana open cultural heritage data, and The Metropolitan Museum of Art Collection API. The collected fields include heritage item names, safeguarding practice descriptions, collection object descriptions, dates, regions, and thematic tags. Cultural policy texts are collected from the official website of China's Ministry of Culture and Tourism and local government policy pages, with emphasis on digital culture, smart tourism, public cultural services, and cultural consumption. Cultural tourism samples are collected from official city tourism websites, public promotional pages, and open event descriptions. All texts are processed through deduplication, abnormal-character cleaning, language normalization, tokenization, entity recognition, and metadata annotation. The final dataset contains a cultural material corpus, a policy constraint corpus, and a communication sample corpus. These three corpora jointly support the later retrieval-augmented generation process, allowing AI-generated texts to be grounded in real cultural materials while being constrained by policy context and communication tasks.

3.2. Generation methods and algorithmic process

The generation process follows a "semantic retrieval, material reconstruction, and LLM generation" pipeline. The cultural material corpus, policy constraint corpus, and communication sample corpus are first divided into semantic segments. Sentence-BERT is then used to obtain vector representations, and FAISS is used to construct the vector index. After each task brief is entered, the system retrieves the most relevant text segments according to cultural objects, communication scenarios, and policy requirements. The retrieved segments and prompt template are then jointly entered into the LLM [10]. To compare different generation mechanisms, three conditions are designed: zero-shot prompting, few-shot prompting, and RAG prompting. Model version, temperature, output length, and task instructions are fixed. Relevant material selection is based on weighted ranking of semantic similarity and term matching, as shown in Formula (1).

$$\text{Score}\,(d_i,q)=\lambda\cdot\cos\,(E(q),E\,(d_i))+(1-\lambda)\cdot BM25\,(q,d_i) \tag{1}$$

Here, d_i denotes a candidate cultural text segment, qqq denotes the task brief, $E(\cdot)$ denotes the Sentence-BERT encoding result, and λ denotes the weight between semantic retrieval and term

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matching. In the generation stage, task instructions, retrieved materials, and prompt constraints are used as joint inputs, as shown in Formula (2).

$$y^{*}=\arg\max_{y} P_{\theta}(y|q,D_{k},p,\tau) \tag{2}$$

Here, d_i denotes the final generated text, D_k denotes the top-k retrieved segments, p denotes the prompt template, τ denotes the temperature parameter, and θ denotes model parameters.

3.3. Evaluation methods and analytical algorithms

The evaluation process focuses on the three types of generated outputs obtained in Section 3.2 and compares the human-only group, AI-assisted group, and fully AI-generated group in terms of efficiency, content quality, and labor substitution intensity. Machine evaluation uses BERTScore, ROUGE-L, Sentence-BERT similarity, and keyword coverage to measure the consistency between generated texts, original cultural materials, task briefs, and policy constraints [11]. Human evaluation is conducted by three reviewers with backgrounds in cultural industries or communication studies. The scoring dimensions include cultural accuracy, expressive attractiveness, originality, and policy suitability, while Cronbach's α is used to test rating consistency. Statistical analysis adopts a two-factor mixed-effects ANOVA, using generation mode and task type as fixed effects and brief ID as a random effect, so as to test quality differences and interaction effects across cultural tasks. Creative labor substitution intensity is calculated by integrating efficiency improvement, quality retention, and risk deduction, as shown in Formula (3).

$$LSI_{j,x}=\left(1-\frac{T_{j,x}}{T_{j,A}}\right)\cdot\frac{Q_{j,x}}{Q_{j,A}}\cdot(1-R_{j,x}) \tag{3}$$

Here, $LSI_{j,x}$ denotes the creative labor substitution intensity of task j under generation mode x, T denotes completion time, Q denotes the comprehensive quality score, R denotes the cultural or policy risk score, and A denotes the human-only baseline group. Random forest regression is used to identify the effects of task complexity, cultural term density, policy constraint quantity, and text length on LSI, while SHAP values explain the contribution of each variable to the substitution boundary.

4. Results

4.1. Production efficiency and content quality

The pilot experiment uses 60 cultural content tasks, with 15 briefs for each task type. The tasks are processed through human-only creation, AI-assisted creation, and fully AI-generated creation. As shown in Table 1, the average completion time of the AI-assisted group is 25.7±6.1 min, which is clearly lower than the 44.2±8.6 min of the human-only group. The number of revision rounds also decreases from 3.1±0.9 to 2.2±0.8, indicating that RAG-supported LLMs can undertake material integration, structural generation, and first-draft rewriting. The comprehensive quality score of the AI-assisted group is 84.1±4.3, higher than the 82.6±4.7 of the human-only group, while BERTScore increases from 0.812±0.034 to 0.835±0.029. The fully AI-generated group has the lowest completion time, at only 7.6±1.8 min, but its comprehensive quality score decreases to 75.3±6.5, and policy

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suitability drops to 3.58±0.52. This indicates that full automation is more suitable for first-draft production and idea expansion, but not for direct public communication without review.

Table 1. Comparison of production efficiency and content quality across generation modes

Generation mode	Completion time/min	Revision rounds	Overall quality/100	BERTScore	Policy suitability/5
Human-only group	44.2±8.6	3.1±0.9	82.6±4.7	0.812±0.034	4.18±0.37
AI-assisted group	25.7±6.1	2.2±0.8	84.1±4.3	0.835±0.029	4.21±0.34
Fully AI-generated group	7.6±1.8	0.4±0.3	75.3±6.5	0.768±0.047	3.58±0.52

4.2. Creative labor substitution intensity

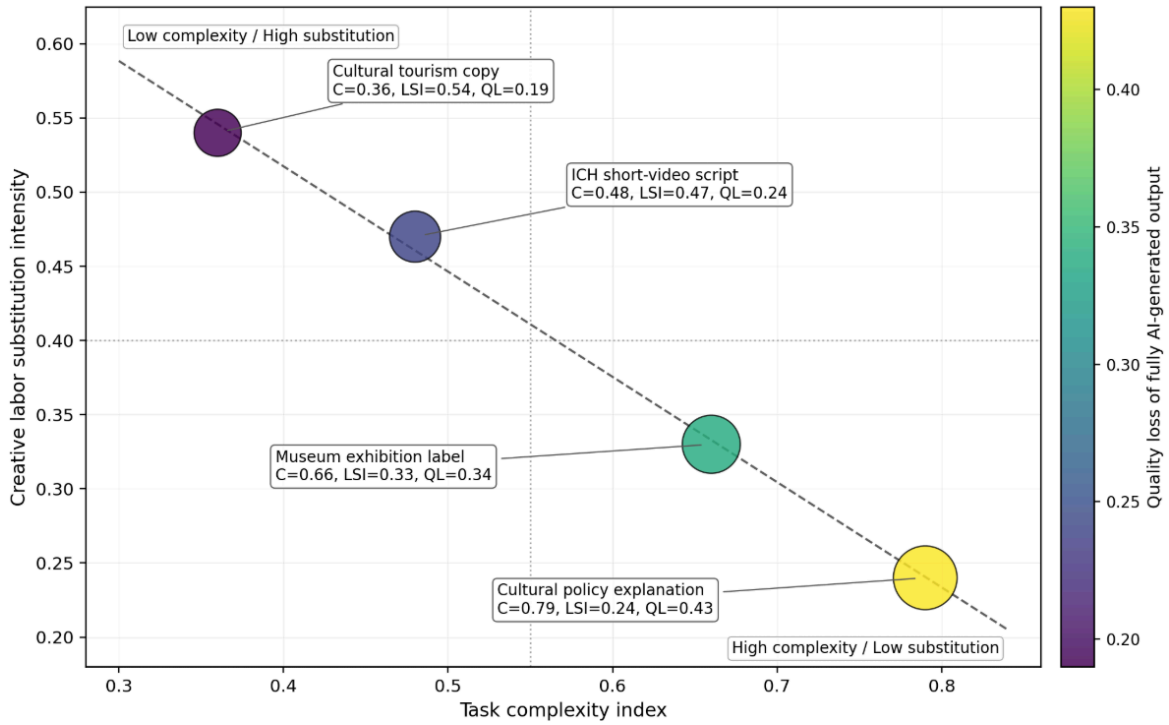


Figure 1. Relationship among cultural task complexity, substitution intensity, and quality loss

Creative labor substitution intensity is presented through task complexity, substitution intensity, and quality loss of fully AI-generated outputs. As shown in Figure 1, cultural tourism copy has a task complexity index of 0.36, a substitution intensity of 0.54, and a quality loss of 0.19. The ICH short-video script has a task complexity index of 0.48, a substitution intensity of 0.47, and a quality loss of 0.24, indicating that tasks with clear structures and stable communication goals are more easily handled by AI. The task complexity of museum exhibition labels increases to 0.66, while substitution intensity decreases to 0.33 and quality loss expands to 0.34. Cultural policy explanation has the highest task complexity index, at 0.79, while substitution intensity is only 0.24 and quality loss reaches 0.43. In the figure, bubble size and color jointly represent quality loss, and the dashed

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trend line shows that substitution intensity decreases as task complexity increases. This suggests that creative labor substitution occurs first in tasks with lower complexity, stronger templates, and lower policy risk.

5. Discussion

The experimental results indicate that generative AI mainly affects cultural content production through workflow compression, task restructuring, and increasing pressure on quality control. The AI-assisted group outperforms the human-only group in time cost and quality score, suggesting that RAG can effectively embed public cultural materials, policy texts, and communication requirements into the generation process, thereby reducing the burden of material collection, first-draft writing, and structural revision. The fully AI-generated group achieves the highest efficiency, but its quality decline is concentrated in policy suitability and cultural accuracy. This reflects the remaining limitations of models in value judgment, contextual interpretation, and public communication responsibility. As substitution intensity decreases with higher task complexity, creative labor substitution is more suitable for standardized, template-based, and lower-risk tasks, while high-context tasks still require human fact-checking, aesthetic selection, and policy review. The results also show that after cultural institutions introduce AI, occupational capabilities do not simply disappear but shift from basic writing to data screening, prompt design, generated-content review, and communication strategy management. At the cultural policy level, AI-use boundaries, data-source labeling, and human review mechanisms should be strengthened to prevent efficiency gains from weakening authenticity and public responsibility in cultural content.

6. Conclusion

This research establishes an experimental framework for analyzing generative AI-driven cultural content production mechanisms and creative labor substitution effects through public data collection, RAG generation, semantic evaluation, expert scoring, and statistical analysis. The results show that AI-assisted production can significantly improve cultural content production efficiency while maintaining stable quality advantages. Fully AI-generated production is suitable for first-draft expansion, but it is less capable of independently completing tasks with strong policy constraints and dense cultural contexts. Creative labor substitution presents clear task differentiation: basic writing and promotional texts are more easily handled by algorithms, while cultural interpretation and policy communication still require human participation. The framework provides methodological support for AI application assessment, occupational skill transition, and cultural policy governance in cultural institutions.

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