International Journal of Computer Information Systems and Industrial Management Applications
ISSN 2150-7988 Volume 18 (2026) pp. 1-12

https://doi.org/10.70917/ijcisim-2026-0038
Article

Market Development and Economic Benefit Analysis of Intangible Cultural Heritage Cultural and Creative Products Empowered by AI

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Abstract: The rise of generative artificial intelligence technology provides a new path for the design innovation and market expansion of non-heritage cultural and creative products. This paper takes AI-enabled non-heritage cultural and creative products as the research object, and systematically explores its market development characteristics and economic benefit enhancement mechanism. Based on generative adversarial network and residual network, the intelligent optimization framework of non-heritage cultural and creative product design is constructed. Through user demand research, perceptual imagery analysis and controlled experiments, the effectiveness of AI technology in improving design efficiency and product quality is verified. Combining the algorithm test and economic benefit assessment of four types of cultural and creative products, namely hand puppet, earrings, fan and book, to reveal the driving effect of AI-enabled on the market competitiveness and economic returns of non-heritage cultural and creative products. After adopting AI-assisted, the economic benefits of each product are significantly improved, and the economic benefits of the hand puppet and earrings show a growing trend, in which the final benefit of the hand puppet reaches 1,312 yuan/d, and that of the earrings reaches 1,118 yuan/d. Adopting AI-assisted styling design of the cultural and creative products is feasible, which not only improves the design effect of the cultural and creative products but also enhances the economic benefits by doing so.

Keywords: non-heritage cultural and creative products; generative adversarial network; residual network; product design; economic benefits

1. Introduction

Intangible cultural heritage (ICH) is an important component of Chinese national culture, carrying rich historical memory, national cultural spirit and national wisdom achievements, and has irreplaceable social value [1-2]. In recent years, cultural and creative industries have risen rapidly around the world and become an important driving force for economic growth and innovation. Cultural and creative design combines cultural elements with modern design concepts to give new service value to cultural and creative products, which are widely favored by the market and consumers [3-4]. Therefore, the integration of non-heritage culture into cultural and creative design gives non-heritage culture a stronger inheritance vitality [5]. The integration of non-heritage and cultural and creative products can make the non-heritage cultural and creative more close to life, closer to the distance between consumers, and better stimulate the consumer's desire for protection, and its importance is undoubted [6-8]. However, due to the constraints of time and space, the presentation of non-heritage cultural and creative products in the past is almost always displayed in exhibition halls, and sales are basically physical store sales [9].

Although the popularity of non-heritage cultural and creative products is increasing, they are not necessities of life, and it is difficult to deliver product information to the audience in time through offline display and sales, and not enough time is left for consumers to understand the products, which affects to a certain extent the broadening of the sales market of non-heritage cultural and creative products [10-12].

With the help of digital technology, the integration of non-heritage cultural content can give non-heritage cultural products greater appeal [13]. Online virtual pavilion display can also be used to present the characteristics and connotations of the products more intuitively to the user, and consumers can seriously understand each product, providing assistance for the innovation of the non-heritage cultural and creative industry [14-15].

In this paper, generative adversarial network is chosen to generate product creative graphics, and residual network is utilized to solve the degradation problem in training. The strategy of AI-enabled non-heritage cultural and creative product design is designed, and user requirements are collected through a questionnaire survey. Introduced perceptual engineering as the evaluation standard to collect and screen emotional vocabulary. The association between emotion vocabulary and product features is obtained using the emotion vocabulary quantization table to provide objective criteria for design selection. Experiments are set up to explore the performance level of the algorithm, and the economic benefits of four types of cultural and creative products are evaluated to reveal the application advantages of AI-enabled application in the optimal design of non-heritage cultural and creative products.

2. AI-Enabled Design Solutions for Non-Heritage Cultural and Creative Products

As an important carrier of China's outstanding traditional culture, the protection and inheritance of intangible cultural heritage has become a core issue of national cultural strategy. In recent years, by virtue of the dual attribute of “culture + consumption”, non-heritage cultural and creative products have become a bridge connecting non-heritage inheritance and market demand. However, traditional non-heritage cultural and creative design faces problems such as low efficiency of creative output, lack of personalization, and disconnection with contemporary aesthetics, which restricts the enhancement of its market competitiveness and economic benefits. In this context, the rapid development of generative artificial intelligence technology provides key technical support for cracking the above dilemma.

2.1. Generating Adversarial Networks

Generative Adversarial Network (GAN) is a deep learning model with the core idea of adversarial training with a binary great great miniaturization strategy.

The simplest generative adversarial network structure consists of a generator (G) and a discriminator (D), and the structure is shown in Figure 1. The generator's task is to learn the input real data or random noise as much as possible, and generate new samples similar to the distribution of the real data, making it difficult to distinguish the generated samples from the real data, and achieving the purpose of deceiving the discriminator. The discriminator, on the other hand, is a binary classifier whose task is to distinguish whether the data input to the discriminator belongs to the real sample or not, and output a probability value indicating the likelihood that the sample belongs to the real data. Through continuous iteration and optimization, the adversarial relationship between the generator and the discriminator drives the performance of both. Eventually, the system reaches an equilibrium state when it is impossible to accurately distinguish the source of the input data, at which point the generator is able to produce high-quality samples that are nearly indistinguishable from the real data.

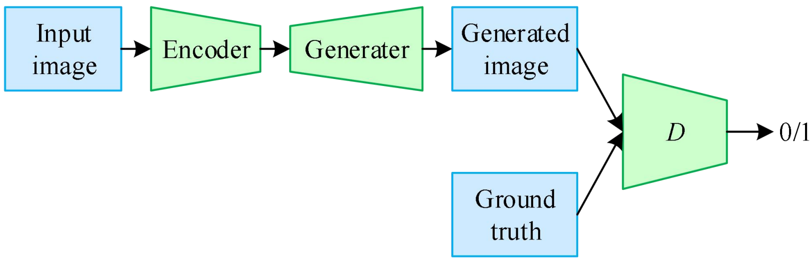


Figure 1. Generative Adversarial Networks.

(1) Realization process

During the training process of generative adversarial network, the generator network and the discriminator network are trained alternately, and the ability of both of them gradually increases until they reach the convergence state. The objective function of this dynamic game process is shown in equation (1):

$$\min_G \max_D V(G,D) = E_{x\sim p(x)}[\log(D(x))] + E_{z\sim p(z)}[\log(1-D(G(z)))] \tag{1}$$

where G and D denote the generator and the discriminator, respectively, $x \sim p(x)$ is the distribution of the real sample x, and $z \sim p(z)$ is the distribution of the input random noise z, which is usually Gaussian. From the objective function equation (1), it can be seen that the objectives of the generator and the discriminator are opposed to each other, the generator pursues to minimize the objective function, while the discriminator pursues to maximize the objective function, which makes the two form a dynamic adversarial game relationship. During the training process, the discriminator faces a non-smooth learning environment, and the generator keeps changing with the training, resulting in the distribution of generated samples also changing. This dynamic change may make it difficult for the discriminator to maintain a good representation of the data. In order to maximize the discriminator's discriminative ability, a common strategy adopted during training is to first fix the generator network parameters and update the discriminator network parameters. At this point, the goal of the discriminator is to make the output $D(x)$ of the real sample x close to 1, while judging the output of the generated sample $G(z)$ close to 0, as shown in equation (2):

$$\max_D V(G,D) = E_{x\sim p(x)}[\log(D(x))] + E_{z\sim p(z)}[\log(1-D(G(z)))] \tag{2}$$

The generator can only optimize the generated sample $G(z)$ through the feedback from the discriminator during the training process, so that the generated sample converges to the distribution of the real sample as much as possible, while the discriminator judges the generated sample $G(z)$ as the real sample, and $D(G(z))$ is as close as possible to 1. However, the generator G can not directly update the parameter weights of the discriminator, and thus the generator's objective function is as shown in Equation (3) is shown:

$$\max_D V(G,D) = E_{z\sim p(z)}[\log(1-D(G(z)))] \tag{3}$$

Eventually, a dynamic equilibrium is gradually reached between the generator and the discriminator through continuous adversarial training, at which time the discriminator cannot effectively distinguish between the generated sample $G(z)$ and the real sample x, and this equilibrium state is called the Nash equilibrium. Nash equilibrium is a game concept that refers to a multi-player decision-making scenario, if each participant is unable to unilaterally change his or her decision to obtain a better result.

(2) Advantages and Disadvantages of Generative Adversarial Networks

GAN is suitable for semi-supervised learning or unsupervised learning and has been widely used in the fields of image generation, image translation, audio generation, etc. It has the advantages of being able to perform end-to-end model building, direct feature extraction and inference on input samples, and mapping simple inputs to high-dimensional spaces. Meanwhile, GAN reduces the network's need for a large number of labeled samples, which can further improve the generalization ability of the model. However, due to the difficulty in optimizing the training process of GAN, it is difficult for the generator and discriminator to achieve Nash equilibrium in adversarial training, which may lead to problems such as unstable training, vanishing gradient, and pattern collapse, which in turn leads to a lack of diversity and poor quality of the generated data, or even training failure.

2.2. Residual Networks

Residual Networks (ResNet) is an important milestone in the field of deep learning, solving the degradation problem in deep neural network training, where the training error rises instead as the number of network layers increases. The core of Residual Networks is the residual block. The idea of the residual block is to introduce a “shortcut” that allows the data to propagate directly bypassing some layers, and its basic structure is shown in Figure 2.

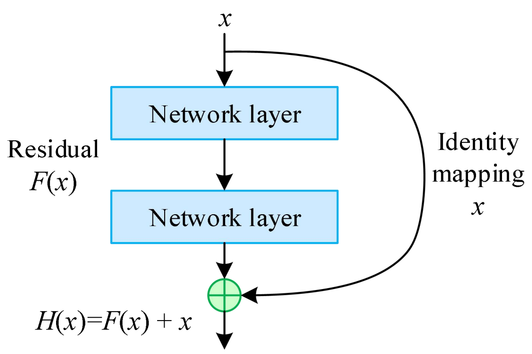


Figure 2. Basic Structure of the residual block.

If the network layers are viewed as mapping functions, x is the input to a segment of the network, $F(x)$ is the function transformation represented by this segment, and $H(x)$ is the output of this segment. The traditional network structure is learned as $H(x)$, as shown in Equation (4):

$$H(x) = F(x) + x \tag{4}$$

The residual network makes $H(x)$ equal to x by constant mapping. Let the learning objective of the network change from $H(x)$ to the "residual" $F(x)$, as shown in equation (5):

$$F(x) = H(x) - x \tag{5}$$

The advantage of learning "residuals" is that if it is difficult to map the input of the network to the target result, you can make $H(x)$ equal to x, so that $F(x)$ is equal to 0, i.e., the network does not exist. This reflects the idea of "guarantee" the residual network, that is, adding more network layers, the performance of the model can remain the same, but not worse. With the idea of "guarantee", ResNet has been a huge success, achieving unprecedented performance on several important visual recognition tasks.

2.3. Strategies for AI-Enabled Non-Heritage Cultural and Creative Product Design

2.3.1. Optimize the Overall Design Process

Optimizing the overall design process refers to the proper selection and application of generative artificial intelligence software in the entire design process of non-heritage cultural and creative products, to work closely with it to carry out comprehensive and in-depth design planning, in order to improve the efficiency of design innovation. With the continuous progress and improvement of generative artificial intelligence technology, it can now customize a set of path planning solutions specifically applicable to the design of non-heritage cultural and creative products based on daily experience and habits. Specifically, taking the design of non-heritage cultural and creative products as the theme, it first utilizes digital capabilities such as big data and deep learning to complete the preparation of creative ideas and the preliminary research stage. Subsequently, the debugged training model is combined with the rich information collected to present the initial display effect of the product. Entering the mass production stage, it is only necessary to easily filter and flexibly adjust the relationship between the model, keywords and reference diagrams to easily collect the required effect reference diagrams, providing strong support for the subsequent design.

2.3.2. Optimization of Specific Design Steps

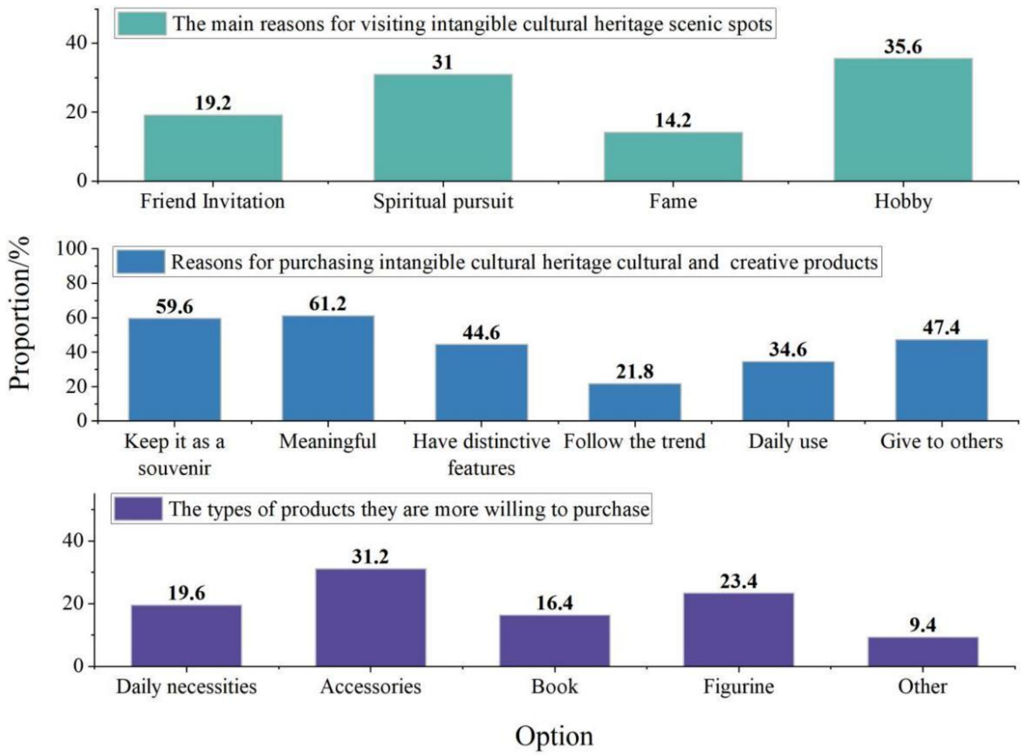
Optimizing specific design steps refers to consciously and systematically selecting and applying generative AI software at specific stages in the design path of non-heritage cultural and creative products to assist in the completion of innovative design tasks. Specifically, the non-creative part of the design of non-heritage cultural and creative products is handed over to the generative AI software for execution. Based on the results of in-depth research and detailed program analysis in the early stage, targeted model training is carried out according to the specific needs of the design. This aims to provide accurate reference data and rich style sampling for subsequent image generation. This process can be carried out in a fragmented form to ensure that the content of the final reference image generated meets the design requirements. In the process of generating images, the selection of keywords and the adjustment of word frames determine the quality of the output image. By setting and adjusting a series of key words such as appearance, color, shape, frame quality, lighting and so on, in order to combine the sketches to generate a variety of styles of effect diagrams. The unique advantage of generative AI technology is that it can quickly respond to changes and extensions in segmentation requirements during the design project, thus improving design efficiency. It also provides a clearer and more efficient path to complement the personalized and small-scale customization needs of non-heritage cultural and creative product design.

3. Research on the Application of Optimized Design of Non-Heritage Cultural and Creative Products Empowered by AI

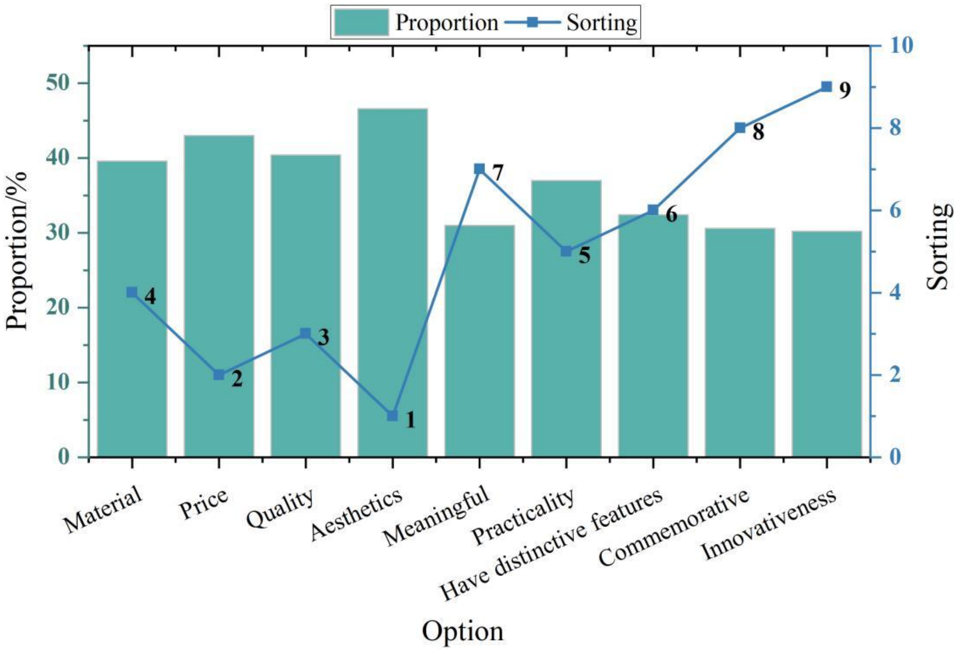
3.1. Feasibility Analysis

3.1.1. User Requirements Research

Studying users' needs not only allows us to understand users' preferences, but also allows us to further study what non-heritage cultural and creative products users should like, and give guidelines for developing non-heritage cultural and creative products. The questionnaire was released through online platforms such as Questionnaire Star, and a total of 509 copies were recovered, removing 7 invalid questionnaires and 2 large blank questionnaires, and finally 500 valid papers were left. The statistical results of user demand and the importance of each aspect of the product are shown in Fig. 3 (a~b). 35.6% of the users traveled to non-heritage attractions for hobby, 59.6% and 61.2% of the users purchased non-heritage cultural and creative products for souvenir and meaningful reasons, respectively, and 31.2% of the users preferred purchasing non-heritage cultural and creative products of the jewelry type. The top three rankings in terms of the importance of each aspect of the product were aesthetics, price and quality, respectively.



(a) User demand



(b) The Importance of products

Figure 3. Results of the user demand research.

3.1.2. Establishment of Selection Criteria

Based on the basic principles of morphological analysis method, this paper takes the fan of cultural and creative products as an example, and systematically disassembles and carefully divides it. Ten samples were surveyed according to the seven-level evaluation table of emotional imagery vocabulary, 200 questionnaires were distributed and 195 questionnaires were returned, of which 190 were valid questionnaires, while the other questionnaires were invalidated due to unfilled or incorrectly filled in. The valid questionnaires of the perceptual evaluation of the fan of the cultural and creative products were exhaustively organized and statistically analyzed, and the average value of the perceptual vocabulary scores of each group was calculated to get the evaluation data of these perceptual vocabularies on 10 samples, and the specific evaluation data are shown in Table 1. Comparing the scores of the perceptual vocabulary of each sample, through the scoring rules, the larger the value represents the closer to the perceptual vocabulary. Taking the term "sensual" as an example, this paper finds that samples 2 and 7 are at a higher level of scoring for this term, while samples 3 and 4 have lower scores.

Table 1. Evaluation data of each sample on perceptual vocabulary.

	Emotional	Simple	Light	Fashionable	Warm	Effortless
Sample 1	0.48	0.55	0.91	0.37	-1.42	-0.56
Sample 2	0.67	0.98	1.22	0.96	1.05	0.93
Sample 3	-0.38	-0.29	-1.34	0.16	0.22	-1.61
Sample 4	0.39	-1.03	-0.97	-1.88	0.22	-1.12
Sample 5	0.22	0.49	0.11	0.26	0.35	0.77
Sample 6	0.31	0.28	-0.94	0.85	0.72	0.19
Sample 7	1.38	1.22	0.97	-0.23	0.76	0.85
Sample 8	0.95	0.37	0.26	0.08	0.19	0.34
Sample 9	1.22	0.94	0.23	-0.88	0.21	0.32
Sample 10	0.29	0.47	0.98	0.12	-0.34	-1.08

Determine the relationship between perceptual vocabulary and morphological elements of the fan for cultural and creative products by analyzing the morphology of the highest scoring samples in each group of vocabulary. Morphological features that are close to the perceptual vocabulary with high scores are adopted as the design requirements, and the images that meet the above requirements are selected for optimization after the images are generated on the web according to the above requirements.

3.1.3. Assessment of Design Effectiveness

The experiment was conducted by using the control group, and the experimental and control groups were set up in 5 groups respectively. This experiment invited the participation of design students, including 20 graduate students and 20 undergraduates, in order to ensure the fairness of the experiment experimental group and control group are 10 undergraduates and 10 graduate students.

Experimental process: firstly, 500 fan pictures were selected as the initial data for generation, the experimental group drew the product effect diagrams according to the generation results, and the control group drew the product effect diagrams with the initial pictures as the reference. The evaluation of the design effect adopts the scoring method of the expert group, which consists of five design experts, and scores whether it conforms to the design orientation as the evaluation criterion, and the scoring method adopts the 5-order Richter scale, and finally adds up the scores of each expert as the final score. In order to avoid expert bias, the design works were disrupted and sent for review, and the evaluation results of 10 groups of works in each of the experimental and control groups are shown in Table 2. The scores of each group are averaged out, and the average score of the control group is 17.3 and the average score of the experimental group is 21.5. The score of the experimental group is much higher than that of the control group, which proves that the use of generative results to assist the design has a good effect, and indirectly proves that the application of generative adversarial network to obtain the creative graphics of the product can improve the design effect.

Table 2. Review Results.

Work Number	Work score	Work Number	Work score
Experimental Group 1	20	Control group 1	18
Experimental Group 2	21	Control group 2	15
Experimental Group 3	23	Control group 3	19
Experimental Group 4	22	Control group 4	21
Experimental Group 5	19	Control group 5	14
Experimental Group 6	24	Control group 6	12
Experimental Group 7	21	Control group 7	19
Experimental Group 8	20	Control group 8	14
Experimental Group 9	22	Control group 9	21
Experimental Group 10	23	Control group 10	20

3.2. Algorithm Testing and Application Analysis

3.2.1. Algorithm Performance Analysis

In the performance analysis of the algorithm, experimental simulation is used to analyze the error of the algorithm improved by the residual network in each axis and to compare the error difference before and after the improvement of the residual network, and the results are shown in Figure 4. It can be seen that the absolute value of the error of the traditional algorithm without residual network is larger, and the absolute value of the evaluation error in each axis reaches 1.16, 0.72, 0.77, respectively. The absolute value of the error of the algorithm proposed in this paper always stays within 0.5, which is a significant reduction in the absolute value of the error of this paper's algorithm compared with the traditional algorithm. The above results show that the algorithm improved by using residual network can effectively reduce the error and enhance its accuracy.

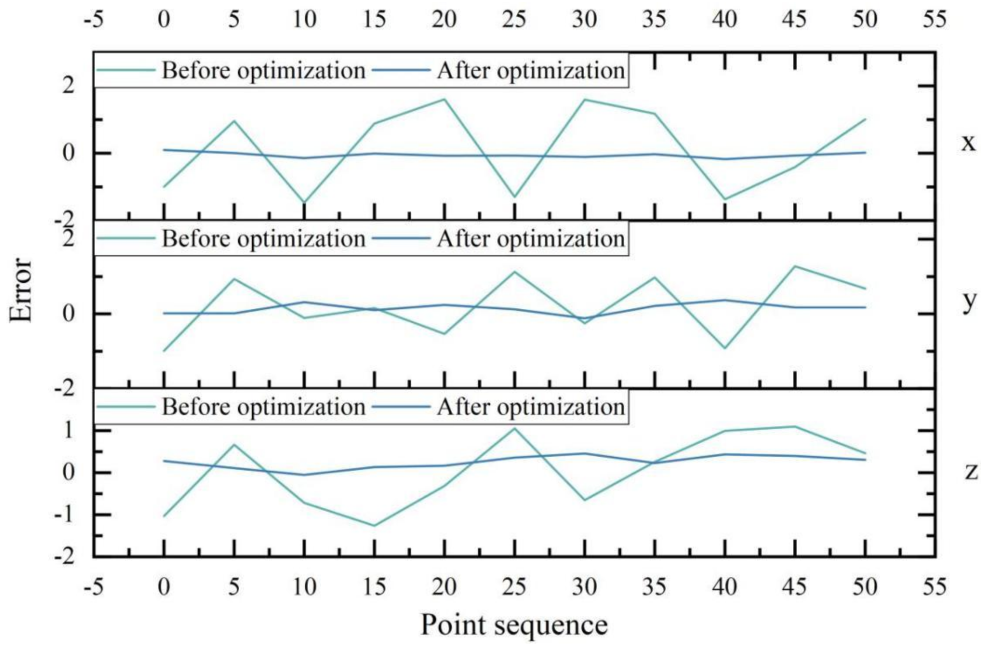
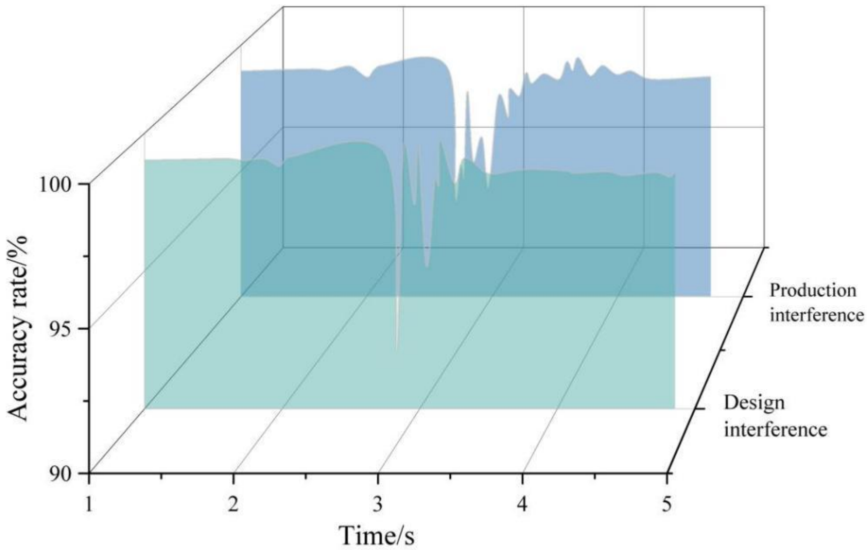
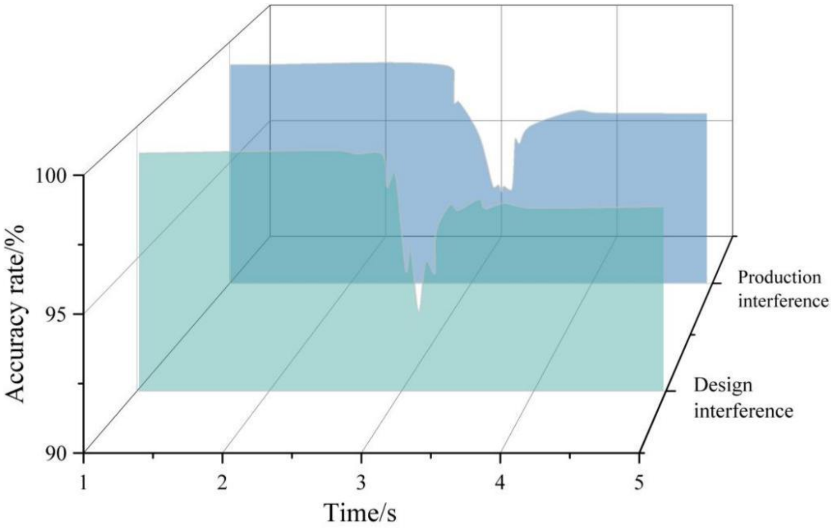


Figure 4. Comparison of algorithm errors.

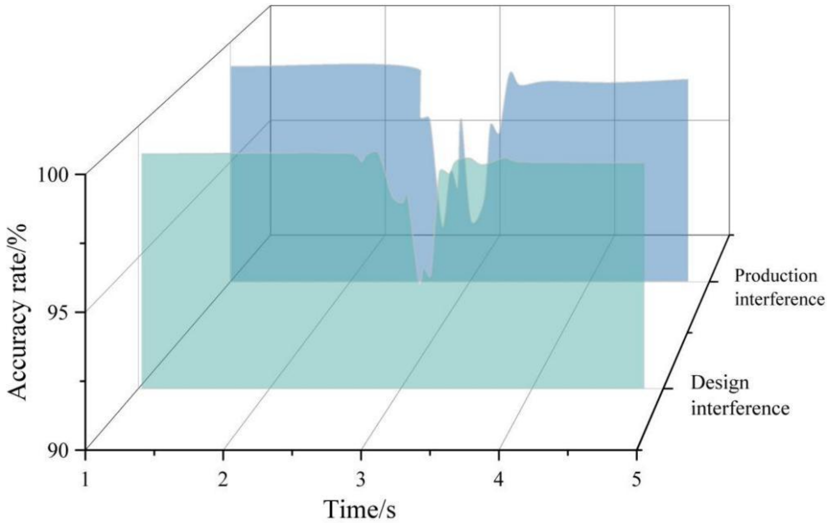
The proposed algorithm is applied to the styling design of four kinds of cultural and creative products, namely, hand puppet, earrings, fan and book, and the anti-interference ability of the algorithm is evaluated in the design of the four kinds of cultural and creative products firstly, and the results of the anti-interference evaluation of the algorithm are shown in Fig. 5(a~d). It can be seen that the stability of the proposed algorithm is strong in different cultural and creative product modeling design. In book modeling design, it is the least affected, and its average accuracy is always higher than 97% after being interfered by many external factors. In the design of earrings, the algorithm is more obviously affected by external factors, and its accuracy is reduced to 92.99%. However, for different types of cultural and creative products, the accuracy of the algorithm is able to recover to a high accuracy rate after the interference, which indicates that the proposed algorithm has high stability.



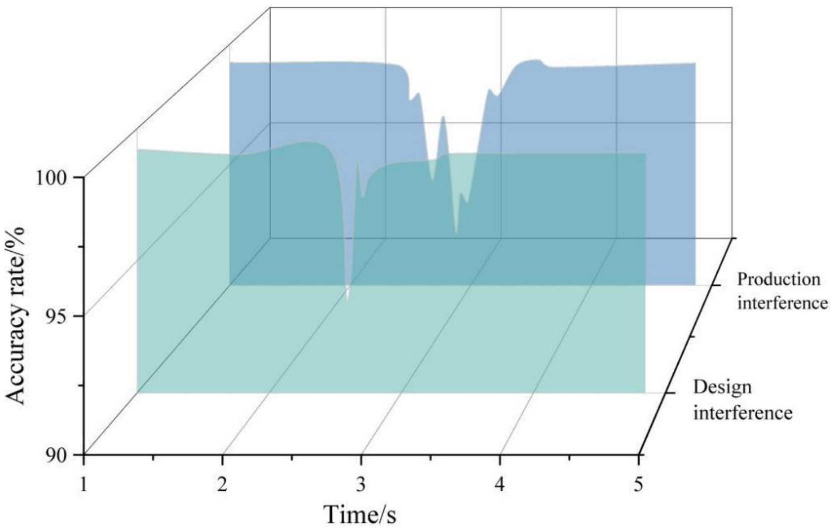
(a) Figurine



(b) Earrings



(c) Fan

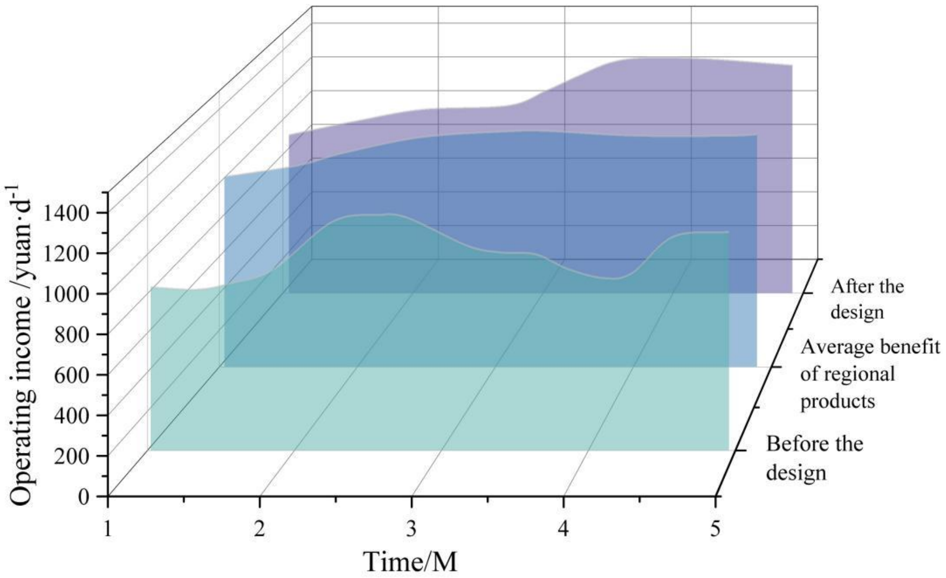


(d) Book

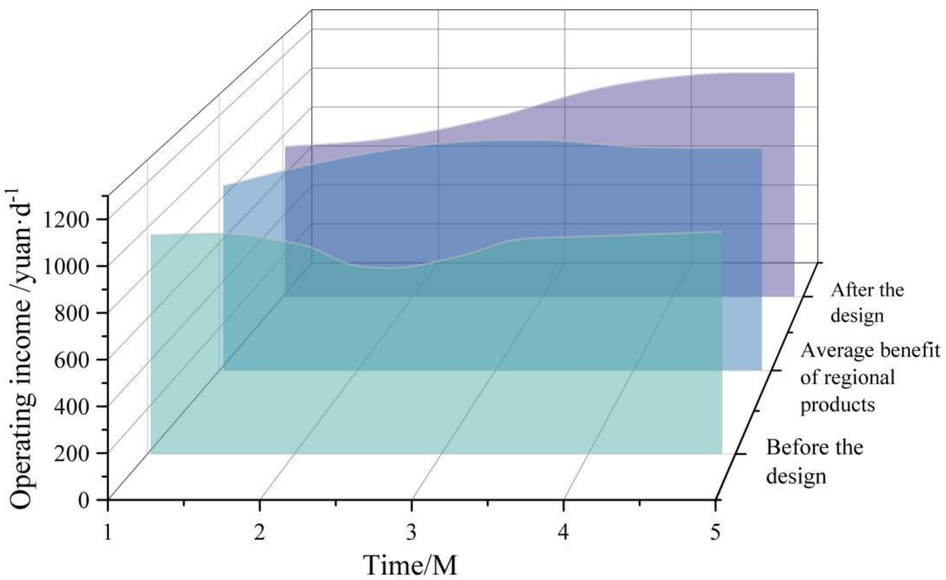
Figure 5. Anti-interference evaluation results of the algorithm.

3.2.2. Application Analysis

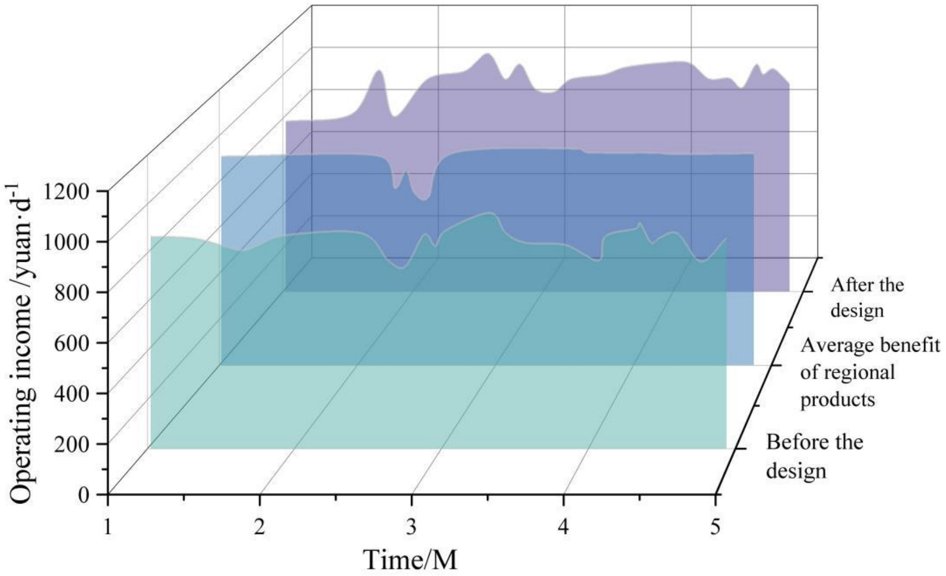
The optimization of styling design of cultural and creative products is not only to improve the production efficiency and quality, but also to ensure its economic benefits in the design is the key to promote cultural inheritance and development. For this reason, this paper evaluates the economic benefits of the styling design of cultural and creative products under AI empowerment at the end, and the evaluation results of the economic benefits of four types of products are shown in Figure 6(a~d). It can be seen that after the adoption of AI empowerment, the economic benefits of each product have been significantly improved, and are significantly higher than the economic benefits of cultural and creative products before design and the average economic benefits of the same type of local products. The economic benefits of the hand puppet and earrings show a growing trend, in which the final benefit of the hand puppet reaches 1,312 yuan/d, and the economic benefit of the earrings reaches 1,118 yuan/d. The above results show that the AI-enabled styling design of the cultural and creative products has a high economic effect under the premise of efficient and high-quality design, and can effectively drive the development of the regional economy.



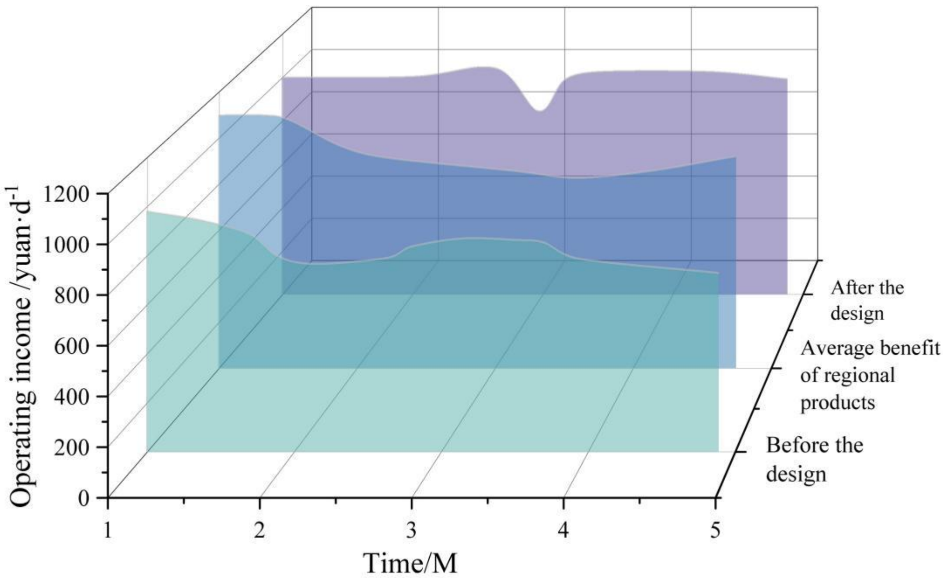
(a) Figurine



(b) Earrings



(c) Fan



(d) Book

Figure 6. Economic benefit evaluation results of four types of products.

4. Conclusion

This paper focuses on the market development and economic benefits of non-heritage cultural and creative products under the empowerment of AI, and systematically reveals the driving role of generative artificial intelligence on non-heritage cultural and creative industry through the construction of technical framework, feasibility verification and application analysis.

In book styling design, the algorithm is least affected, and its average accuracy is always higher than 97% after being interfered by external factors. In the earrings modeling design, the algorithm is more obviously affected by the outside world, and its maximum accuracy rate is reduced to 92.99%. After adopting AI, the economic benefits of each product are significantly improved, and are significantly higher than the economic benefits of cultural and creative products before design and the average economic benefits of local products of the same type. The economic benefits of the hand puppet and earrings show a growing trend, in which the final benefit of the hand puppet reaches 1,312 yuan/d, and the economic benefit of the earrings reaches 1,118 yuan/d. The AI-enabled styling design of the cultural and creative products has a high economic effect under the premise of high design efficiency and high quality, which can effectively drive the development of the regional economy.

References

1. Baicui, X. U., & Jinghu, P. A. N. (2018). Spatial distribution characteristics of the intangible cultural heritage in China. Economic geography, 38(5), 188-196.
2. Zhang, J. (2017). Intangible cultural heritage and self-healing mechanism in Chinese culture. Western Folklore, 197-226.
3. Liang, Y., & Qi, Z. (2021). Research on Innovative design of tourism cultural and creative products from the perspective of Huizhou intangible cultural heritage culture: Taking wood carving patterns as an example. Sci. Soc. Res, 3, 228-232.
4. Petronela, T. (2016). The importance of the intangible cultural heritage in the economy. Procedia Economics and Finance, 39, 731-736.
5. Lei, Z., & Jialing, W. (2024). The Impact of Cultural and Creative Products Arising from Intangible Cultural Heritage on Economic Development: A Case Study of Ebian County, China. Journal of Resources and Ecology, 15(4), 1106-1112.
6. Rodrigues, C., Liberato, D., & Esteves, E. (2022). The intangible cultural heritage as a creative tourism product. The masks of Trás-os-Montes. In Advances in Tourism, Technology and Systems: Selected Papers from ICOTTS 2021, Volume 1 (pp. 595-609). Singapore: Springer Nature Singapore.
7. Meng, Q. (2023). Research on the integration of intangible elements and cultural and creative product design. Frontiers in Art Research, 5(8), 70-75.
8. Erlewein, S. (2015). Sustainable development and intangible cultural heritage: Integrating culture into development. Perceptions of sustainability in heritage studies, 71-83.
9. Tan, S. K., Lim, H. H., Tan, S. H., & Kok, Y. S. (2020). A cultural creativity framework for the sustainability of intangible cultural heritage. Journal of Hospitality & Tourism Research, 44(3), 439-471.
10. Liang, D. (2022). Aesthetic value evaluation for digital cultural and creative products with artificial intelligence. Wireless Communications and Mobile Computing, 2022(1), 8318620.
11. Hsieh, Y. Y., Chen, C. C., Chen, W. Y., & Cheng, T. Y. (2024). The future development trends of Taiwan cultural and creative products from the perspective of industrial design. Creative Industries Journal, 17(1), 60-74.
12. Yang, L., & Huang, E. (2024). Innovation in Marketing Strategies for Museum Cultural and Creative Products Under New Consumer Demand. Journal of Humanities, Arts and Social Science, 8(3).
13. Mihelj, S., Leguina, A., & Downey, J. (2019). Culture is digital: Cultural participation, diversity and the digital divide. New media & society, 21(7), 1465-1485.
14. Yan, J., Shan, X., & Xu, X. (2024). Research on digital display design strategy of Jingdezhen ceramic cultural and creative products. The Frontiers of Society, Science and Technology, 6(7).
15. Li, C. (2024, May). Enshi Yulu Tea Cultural and Creative Product Design Based on AHP Hierarchical Analysis Method. In Proceedings of the 2024 International Conference on Computer and Multimedia Technology (pp. 212-216).