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Human–AI Collaborative Decision-Making for Ceramic Cultural Heritage Product Design: An Integrated AHP–AlexNet Framework

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ABSTRACT

Against the backdrop of globalisation and accelerating digital transformation, the creative redesign of ceramic intangible cultural heritage (ICH) encounters persistent challenges, including inefficient subjective evaluation and the difficulty of simultaneously preserving cultural significance and achieving visual appeal. To overcome these limitations, this study develops an integrated decision-support framework that combines the Analytic Hierarchy Process (AHP) with the AlexNet convolutional neural network (CNN) to improve the evaluation and selection of ceramic ICH creative products. The research first establishes a multidimensional assessment framework encompassing cultural inheritance, visual aesthetics, human-centred ergonomics, and innovation potential. By integrating Kansei Engineering with AHP, the framework ensures that design decisions remain aligned with traditional cultural values while satisfying engineering ethics and functional requirements. Subsequently, a transfer learning approach is employed to optimise the AlexNet model using a purpose-built ceramic aesthetics dataset comprising 24,000 high-quality samples. This enables the deep learning model to perform rapid and objective quantification of complex visual characteristics. A comprehensive comparative evaluation is conducted against widely adopted deep learning architectures, including VGG-16 and ResNet-50. The findings demonstrate that AlexNet delivers the most favourable trade-off between computational efficiency and aesthetic feature extraction accuracy, achieving a validation mean squared error of 0.4912 and a Pearson correlation coefficient of 0.875. Furthermore, the ablation experiments reveal that the proposed subjective-objective score mapping mechanism effectively mitigates both the cultural disconnect associated with purely algorithmic evaluation and the subjective inconsistencies inherent in conventional manual assessment during the selection of 100 conceptual blue-and-white porcelain stationery designs. Overall, the proposed framework establishes a comprehensive human–machine collaborative decision-making approach that spans theoretical development, implementation methodology, and quantitative performance evaluation. The study offers a robust and scientifically grounded solution for ceramic craftsmanship, creative product design, and the wider digital transformation of ICH.

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1. Introduction

Driven by accelerating globalisation and digital transformation, the preservation, transmission, and value reconstruction of ICH within contemporary commercial ecosystems have emerged as a prominent interdisciplinary research focus. Ceramic craftsmanship, recognised as one of the most distinguished cultural expressions in human civilisation, embodies rich historical traditions, artistic aesthetics, and artisanal expertise while serving as a valuable resource for the modern CCI. With the continued convergence of the cultural and tourism sectors, museums, heritage institutions, and tourist destinations increasingly utilise ceramic cultural products to communicate cultural significance while generating economic value [1; 2]. Despite this growing interest, the design and development of ceramic cultural products continue to encounter substantial structural challenges. The market is saturated with highly homogeneous products that rely on superficial replication of cultural motifs, limiting their ability to satisfy increasingly sophisticated and personalised consumer preferences. Simultaneously, numerous traditional ceramic practices within ICH, including Jingdezhen blue-and-white porcelain craftsmanship and Thailand’s Sangkhalok ceramics, face an escalating risk of declining relevance because effective mechanisms for adapting these traditions to contemporary lifestyles remain insufficient [1; 3-5].

Conventional product design largely depends on designers' individual judgement or the subjective evaluation of a limited panel of domain specialists when generating and selecting creative concepts [6; 7]. To formalise these implicit design judgements, KE has been extensively adopted to capture users' emotional perceptions of product appearance and systematically translate them into measurable design attributes [6; 7]. Within this framework, Multi-Criteria Decision Making (MCDM) techniques, particularly AHP, are frequently employed to establish structured evaluation models capable of assigning relative importance to cultural representation, aesthetic quality, and functional performance [8; 9]. Although AHP effectively organises subjective knowledge and facilitates consensus among experts, several limitations restrict its practical applicability. The construction of pairwise comparison matrices remains heavily dependent on expert judgement, increasing susceptibility to cognitive bias and subjective inconsistency. Furthermore, the rapid advancement of Artificial Intelligence Generated Content (AIGC) has enabled the automatic generation of hundreds or even thousands of design alternatives within a short period. Under such circumstances, traditional AHP-based manual evaluation becomes impractical owing to excessive computational demands, substantial time requirements, and inconsistent scoring outcomes [10].

Recent advances in computer vision and deep learning have created new opportunities to overcome the efficiency limitations associated with conventional subjective assessment. CNN-based architectures, exemplified by AlexNet, emulate the hierarchical information processing of the human visual system by progressively learning representations ranging from low-level edge patterns to high-level semantic characteristics from complex image data [11]. Since its landmark success in the 2012 ImageNet competition, AlexNet has demonstrated remarkable capability across numerous vision-related applications, including Image Aesthetic Assessment (IAA), style recognition, and industrial defect detection [12; 13]. Compared with deeper architectures, such as ResNet and VGG, AlexNet provides a favourable balance between network complexity and learning capacity, enabling efficient extraction of fine-grained visual features while reducing the likelihood of overfitting when trained on relatively limited datasets [14]. Although recent studies have explored deep learning for objective prediction of product aesthetic quality, applications involving ICH remain constrained because purely vision-based models primarily evaluate visual composition while overlooking the historical narratives, cultural identity, symbolic significance, and production feasibility embedded within traditional craftsmanship [15; 16].

In response to these research gaps and practical challenges, this study develops an integrated AHP–AlexNet decision framework to enhance the design and evaluation of ceramic cultural products [2; 13]. The proposed framework is founded on the premise that successful cultural products should simultaneously embody profound cultural meaning and superior visual quality. Accordingly, AHP is employed to establish subjective evaluation criteria that emphasise cultural continuity, functional performance, and market-oriented innovation, thereby ensuring that design decisions remain consistent with cultural authenticity and engineering ethics. Concurrently, transfer learning is applied to optimise AlexNet using domain-specific aesthetic datasets, enabling the model to function as a virtual aesthetic evaluator capable of automatically assessing extensive collections of candidate designs. By integrating subjective expert judgements with objective visual predictions through a logically consistent score-mapping mechanism, the proposed framework substantially enhances the efficiency, consistency, and scientific validity of design selection. Moreover, it elucidates the complementary interaction between human cultural expertise and machine-driven visual intelligence, thereby providing both a robust theoretical framework and a practical decision-support tool for advancing the digital transformation of traditional ceramic craftsmanship (Fig. 1).

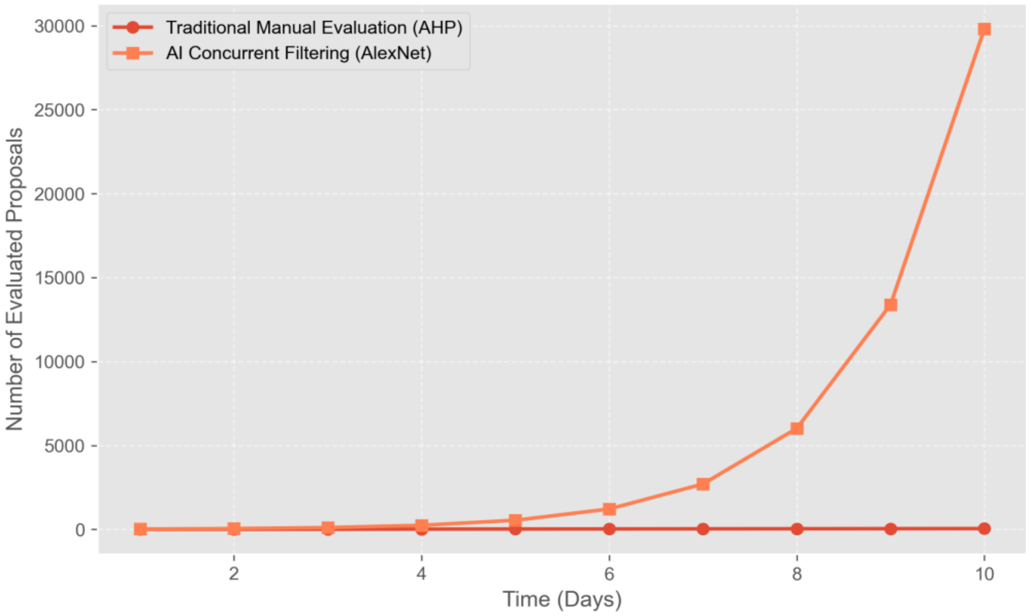

Fig.1: Comparison Trend Chart of Evaluation Efficiency Between Traditional Manual Assessment and AI Concurrent Generation Approach

2. Theoretical Evolution and Literature Review

2.1. Digital Survival and Modern Design Transformation of Intangible Cultural Heritage of Ceramics

Ceramic craftsmanship, recognised as a cultural legacy with a history spanning several millennia, has gradually evolved from an emphasis on preserving traditional techniques towards promoting living heritage and commercial revitalisation. Existing studies suggest that, within an increasingly globalised consumer market, traditional ceramic forms, glazing techniques, and decorative motifs must be adapted to contemporary lifestyles to sustain their cultural relevance and market competitiveness [16]. Jingdezhen, widely acknowledged as the world's "Porcelain Capital", exemplifies this transformation. Home to more than 3,200 recognised ICH inheritors, the region has increasingly incorporated advanced digital technologies into heritage conservation. Recent developments have introduced AI-assisted design generation and three-dimensional (3D) printing into ceramic concept development and complex structural fabrication, substantially lowering the technical barriers for non-specialist designers to participate in interdisciplinary creative innovation [17]. Furthermore, studies have demonstrated that digital technologies, including 3D scanning and multispectral imaging, facilitate the establishment of comprehensive digital heritage repositories, providing sustainable resources to support subsequent product development and creative design activities [5].

Nevertheless, transforming ceramic traditions originating from diverse cultural contexts involves considerably more than simply combining visual elements. Previous research has applied cultural gene theory and symbolic semantics to classify ceramic ICH into three interconnected dimensions: the material dimension, encompassing form and material characteristics; the behavioural dimension, including firing techniques and usage rituals; and the spiritual dimension, representing symbolic meanings and philosophical values [4]. Within this perspective, the development of cultural products is conceptualised as a process of encoding and decoding cultural information across different historical periods. Despite these conceptual advances, significant limitations persist. When designers reconstruct cultural elements into new product forms, existing approaches provide limited capability to quantitatively determine whether the redesigned products simultaneously preserve authentic cultural identity and satisfy contemporary aesthetic expectations. The absence of an objective validation mechanism has constrained much of the existing research into conceptual discussions, thereby limiting its applicability to large-scale industrial implementation.

2.2. Collaboration Between Multi-Criteria Decision-Making and Kansei Engineering in the Product Evaluation System

To overcome the challenge of quantifying design evaluation, KE provides an effective framework for linking consumers' psychological perceptions with the physical attributes of products. During the early stages of product development, KE gathers Kansei Words from target users to establish an evaluation space that captures subjective emotional responses towards product appearance [6; 7]. To determine the relative importance of these emotional dimensions objectively, MCDM techniques, particularly AHP, are commonly incorporated into the evaluation framework [18].

Originally introduced in the 1970s, AHP simplifies complex decision-making by decomposing problems into hierarchical levels comprising the goal, criteria, and alternatives. Pairwise comparison matrices are constructed using the nine-point scale, enabling the calculation of relative weights for each evaluation criterion [8; 9]. Within research on cultural and creative products, AHP is frequently integrated with complementary decision-making approaches to improve analytical rigour and systematically accommodate multiple evaluation perspectives. For instance, the KANO–AHP–DEMATEL–VIKOR framework has been developed to reduce subjectivity in museum cultural product design by identifying consumers' primary preferences while simultaneously revealing the causal relationships among different evaluation criteria [19].

Similarly, studies focusing on tourism-related cultural products have combined the KANO model with AHP to refine an initial set of 80 user requirements, ultimately identifying historical heritage, regional identity, and practical functionality as the three most influential design dimensions [3]. Despite its substantial contribution to structuring complex decisions and balancing multiple design considerations, AHP remains inherently dependent on subjective expert judgement. Its effectiveness diminishes when assessing subtle visual variations, such as slight modifications in line curvature or minor adjustments in colour intensity, because these fine-grained differences are difficult to distinguish consistently through manual scoring. Moreover, the method lacks the capability to automatically evaluate large-scale collections of design alternatives, making it unsuitable for high-throughput design assessment.

2.3. The Evolution of Convolutional Neural Networks and Deep Learning in Image Aesthetics

The emergence of deep learning has fundamentally reshaped computer vision by replacing manually engineered feature extraction methods, such as Scale-Invariant Feature Transform (SIFT) and Histogram of Oriented Gradients (HOG), with data-driven representation learning capable of automatically identifying discriminative visual features [4; 20]. Following the introduction of AlexNet in 2012, which dramatically improved ImageNet classification performance, deep learning has rapidly advanced across numerous computer vision applications, including image recognition, style transfer, and aesthetic evaluation [12; 13].

IAA represents one of the most demanding computer vision tasks because it requires a model to recognise image content while simultaneously evaluating its aesthetic quality. Contemporary approaches typically formulate IAA as either an image classification problem or a regression task that predicts aesthetic scores using deep CNNs [21]. Although deeper architectures, including VGG-16, ResNet-50, and Xception, have achieved outstanding performance on large-scale natural image classification benchmarks [11], their superiority is not always maintained in specialised design applications, such as automotive styling, packaging design, and ceramic art evaluation. Within these domain-specific contexts, AlexNet continues to exhibit distinct architectural advantages. Comparative research evaluating ResNet-50, VGG-16, and AlexNet for industrial styling assessment reported that, although ResNet-50 achieved a marginally lower validation MSE, AlexNet demonstrated faster convergence and superior overall computational efficiency during training while exhibiting greater robustness against gradient degradation and overfitting when learning from relatively small, specialised datasets [14]. Furthermore, the sequential convolutional and max-pooling operations employed by AlexNet have proven particularly effective in capturing global compositional structures and texture characteristics, closely reflecting the fundamental visual processing mechanisms of the human visual cortex [15; 22].

2.4. Integration of Research Perspectives and Theoretical Breakthrough of this Paper

The existing literature reveals a clear methodological divergence in the study of ceramic cultural products. One stream of research emphasises the qualitative interpretation of cultural symbols and subjective evaluation frameworks, including AHP, whereas others concentrate on applying advanced deep learning techniques for automated image assessment through supervised or unsupervised learning. However, the distinctive characteristics of cultural products require aesthetics to be interpreted alongside cultural significance rather than in isolation. Purely objective algorithms are unable to determine whether a visually harmonious ceramic pattern conflicts with cultural traditions or ethnic taboos, whereas solely expert-driven assessments lack the scalability required to evaluate the rapidly expanding number of design alternatives generated in digital design environments. To address this gap, the present study introduces, for the first time, a heterogeneous subject–objective integrated evaluation topology for ceramic ICH creative products [2; 13]. Within this framework, AHP establishes the primary evaluation criteria governing cultural authenticity, functional performance, and innovation, while AlexNet is responsible for high-throughput visual feature extraction and objective aesthetic assessment. By integrating these complementary capabilities, the proposed framework overcomes the limitations associated with relying on a single evaluation model and provides a practical implementation pathway for Human–AI Collaboration in creative design [23].

3. Experimental Theoretical Framework and Mathematical Model Derivation

To systematically improve both the efficiency and accuracy of evaluating ceramic ICH creative products, this study develops an integrated multi-module evaluation framework. The proposed framework comprises four sequential stages arranged in a top-down workflow:

3.1. Experimental Theoretical Foundation: The Validity Boundary of Objective-Subjective Fusion Decision Making

The integration of AHP and AlexNet extends beyond a simple combination of two analytical techniques and instead represents a complementary framework grounded in information theory and cognitive psychology. Conventional product design evaluation depends heavily on manual assessment, requiring substantial time and human effort while remaining vulnerable to evaluator fatigue and subjective inconsistency. Incorporating CNN-based automated feature extraction and aesthetic prediction substantially improves the efficiency of processing large collections of design alternatives and reflects the emerging direction of intelligent design evaluation and industrial design education. Within the proposed framework, AHP is particularly suited to evaluating discrete semantic dimensions, such as cultural inheritance, because these judgements rely on expert knowledge and high-level cognitive reasoning. In contrast, AlexNet functions as a nonlinear mapping model that learns complex visual representations directly from data distributions [21].

This complementary relationship is especially advantageous for specialised design datasets characterised by intricate local textures, including ceramic glaze transitions and complex ICH decorative patterns, where the number of available training samples is often limited. Owing to its balanced network complexity, AlexNet can effectively capture low-level spatial topological features while exhibiting greater resistance to overfitting than substantially deeper architectures. Consequently, the proposed framework establishes a clear division of responsibilities in which human expertise governs cultural interpretation, whereas AI performs objective visual assessment. This theoretically grounded allocation provides a robust foundation for the mathematical modelling framework developed in the subsequent sections [15; 22].

3.2. Construction of Subjective Evaluation System Based on AHP and Weight Calculation

The competitive advantage of cultural and creative products depends on their capacity to communicate cultural significance while fulfilling functional requirements. To establish a rigorous and comprehensive evaluation framework, this study initially adopted the Delphi method. Hierarchical evaluation indicators relevant to the research objectives were identified through a combination of frequency analysis of the existing literature and multiple rounds of in-depth consultations with 10 experts, including ceramic ICH inheritors, experienced industrial designers, and directors responsible for cultural and creative market operations. The resulting evaluation framework comprises three hierarchical levels: the target layer, representing the comprehensive design optimisation of ceramic cultural products; the criterion layer, consisting of four primary dimensions; and the alternative layer, containing 12 secondary evaluation indicators.

- Cultural Heritage and Inheritance (C1): This dimension evaluates the extent to which a product preserves the cultural essence of ceramic ICH. It comprises Symbol Restoration Accuracy (C11), Regional Cultural Recognition (C12), and ICH Skill Correlation (C13).
- Visual Aesthetics and Artistry (C2): This dimension measures the overall visual quality of the product and is subsequently evaluated objectively using AlexNet. It includes Shape Proportion Coordination (C21), Colour Harmony (C22), and Pattern Layout Balance (C23).
- Human–Machine Ergonomics and Practicality (C3): This dimension assesses the product's usability and physical performance as a functional object. It consists of Grip and Usage Comfort (C31), Material Durability and Safety (C32), and Manufacturing Feasibility (C33).
- Innovation Potential and Marketability (C4): This dimension estimates the commercial viability and future development potential of the product. It comprises Cross-Domain Concept Integration (C41), Alignment with Consumer Trends (C42), and Expandability of IP-Based Derivative Products (C43).

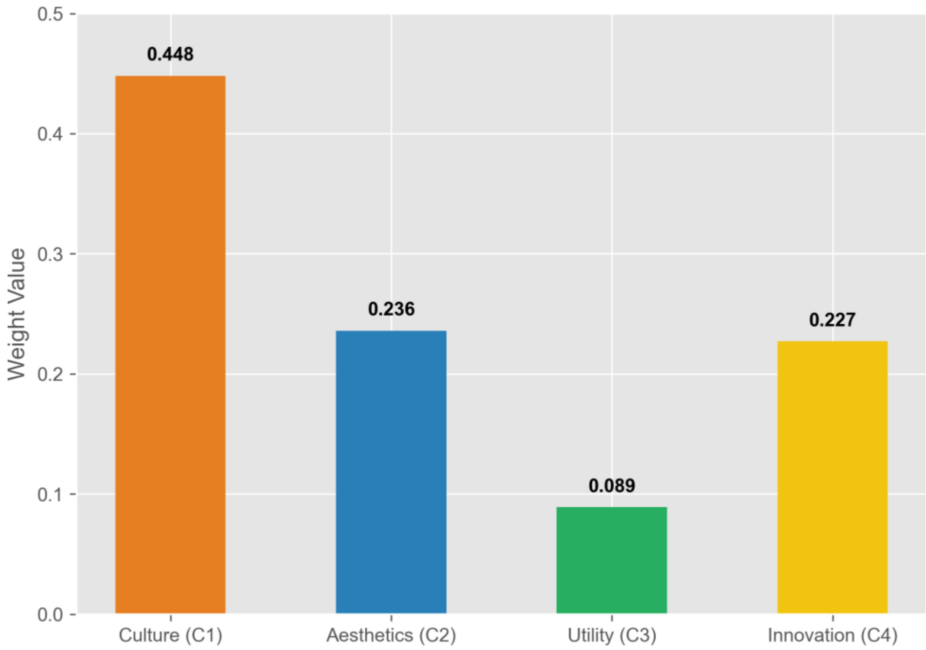

Fig.2: Global Weight Distribution Map of Each First-Level Evaluation Indicator of AHP

Based on the established evaluation hierarchy, AHP questionnaires were administered to the expert panel (Fig. 2). Using Saaty's nine-point scale, where 1 represents equal importance, 9 denotes extreme importance, and reciprocal values indicate the opposite preference, the experts performed pairwise comparisons among indicators within the same hierarchical level. For a hierarchy containing n evaluation indicators, the corresponding pairwise comparison results can be represented by an n × n judgement matrix, A, as expressed in Eq. (1):

$$A = \begin{bmatrix} 1 & a_{12} & \cdots & a_{1n} \\ 1/a_{12} & 1 & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ 1/a_{1n} & 1/a_{2n} & \cdots & 1 \end{bmatrix} \tag{1}$$

In the mathematical derivation, by solving the characteristic equation of the judgment matrix A, which is $Aw = \lambda_{max}w$, the maximum eigenvalue λ_{max} and its corresponding normalized eigenvector w can be obtained. This vector is the set of relative weights of each evaluation index, denoted as $W = (w_1, w_2, \ldots, w_n)^T$.

To minimise logical inconsistencies in the pairwise comparisons provided by the experts, the constructed judgement matrix was subjected to a consistency assessment. This procedure evaluates the internal coherence of the comparison results and verifies the reliability of the derived indicator weights. The corresponding consistency measures are calculated using Eqs. (2) and (3):

$$CI = \frac{\lambda_{max} - n}{n-1} \tag{2}$$

$$CR = \frac{CI}{RI} \tag{3}$$

In these expressions, CI denotes the Consistency Index, whereas RI represents the Random Consistency Index, whose value depends on the order of the judgement matrix. The consistency of the pairwise comparisons is evaluated using the Consistency Ratio (CR). According to the accepted AHP criterion, the judgement matrix is considered logically consistent only when CR is less than 0.10. Under this condition, the derived indicator weights are regarded as reliable and suitable for subsequent decision-making analysis.

3.3. Objective Visual Feature Extraction Network Based on AlexNet Architecture

In the traditional AHP process, Visual Aesthetics and Artistry (C2) is typically assessed through expert visual judgement. However, manual evaluation becomes highly inefficient when many design images must be analysed. To address this limitation, the present study integrates AlexNet into the evaluation framework, enabling the aesthetic dimension to be assessed automatically through a fully quantitative process instead of manual scoring [4; 20].

Network Topology Design: Specifically, AlexNet comprises approximately 60 million trainable parameters and performs nearly 724 million floating-point operations (FLOPs). The architecture introduced two important innovations, namely the Rectified Linear Unit (ReLU) activation function and Dropout regularisation, allowing it to achieve an effective balance between feature representation capability and computational efficiency during image classification and aesthetic analysis. The AlexNet architecture adopted in this study consists of five convolutional modules followed by three fully connected modules.

- Input Processing: To ensure consistent data processing, all ceramic cultural product images are first pre-processed using bilinear interpolation before being cropped and resized to a standard input tensor of 227 × 227 × 3, corresponding to the three RGB colour channels.
- Feature Extraction Layer (Convolution and Pooling):
    - The first convolutional layer (Conv1) applies 96 convolutional filters of size 11 × 11 × 3 with a stride of 4 to rapidly reduce the spatial resolution of the input while extracting coarse global contours and prominent edge features. The resulting feature maps are processed using the ReLU activation function, followed by a 3 × 3 max-pooling layers with a stride of 2 and LRN.
    - The second convolutional layer (Conv2) employs 256 convolutional filters of size 5 × 5 with a stride of 1 to capture increasingly detailed visual representations.
    - The third, fourth, and fifth convolutional layers (Conv3, Conv4, and Conv5) utilise 384, 384, and 256 convolutional filters, respectively, each with a kernel size of 3 × 3. These successive small-kernel convolution operations enable the network to identify highly detailed texture information and subtle variations in light and shadow across ceramic surfaces (Wang et al., 2016). Following Conv5, a further 3 × 3 max-pooling layers is applied, after which the resulting high-dimensional feature maps are flattened into a one-dimensional feature vector for subsequent processing.
- Semantic Mapping and Regression Output Layer (Fully Connected Layer):
    - The network back-end comprises two fully connected hidden layers, FC6 and FC7, each containing 4096 neurons. To reduce the risk of overfitting on the relatively limited training dataset, a Dropout layer is incorporated between these two fully connected layers. During each forward propagation, neurons are randomly deactivated with a probability of 0.5.
    - Architecture Fine-Tuning: Since the original AlexNet employs FC8 as a Softmax classification layer for discrete category prediction, whereas the objective of this study is continuous aesthetic score prediction (a regression task), FC8 was replaced with a linear output layer containing a single neuron.

Loss Function and Optimization Strategy for Transfer Learning: Owing to the relatively limited size of the high-quality labelled aesthetic dataset for ceramic cultural products, training the network from randomly initialised weights may lead to poor convergence. Therefore, this study adopts a transfer learning strategy by loading pre-trained model weights as the initial parameters, freezing the first three convolutional layers, and fine-tuning only the remaining two convolutional layers together with the fully connected layers using the target-domain dataset [12; 13]. The optimisation objective is to minimise the Mean Squared Error (MSE) loss between the predicted aesthetic scores and the corresponding human evaluation scores, as expressed in Eq. (4):

$$L_{MSE} = \frac{1}{N}\sum_{i=1}^{N}(\hat{y}_i - y_i)^2 \quad (4)$$

Here, N represents the size of the mini-batch sample, $\hat{y}_i$ is the continuous aesthetic prediction value given by the AlexNet model, and y_i is the actual aesthetic benchmark score.

3.4. Multidimensional Fusion Mechanism for Heterogeneous Data Using AHP-AlexNet

At this stage, we integrate the expert subjective scores extracted by AHP and the objective visual scores output by AlexNet into a unified decision space. Suppose for any candidate ceramic cultural and creative design scheme X_j, its evaluation score is composed of two parts:

1. Non-Visual Dimension Expert Scoring Set: Based on the AHP index system, the expert database gives scores for the three dimensions of the scheme - cultural heritage (S_{1j}), human-computer usability (S_{3j}), and innovative market (S_{4j}).
2. Visual Dimension Algorithm Scoring: The trained AlexNet network outputs an aesthetic prediction score (S_{2j}) for the scheme's image.

Before integrating the evaluation results, it is necessary to account for potential differences in the scoring scales adopted by the individual assessment modules. Accordingly, the Min–Max normalisation method is applied to transform all scores into a unified dimensionless range of [0, 100], thereby ensuring consistency and comparability across the integrated evaluation framework, as expressed in Eq. (5):

$$S_{ij}^{'} = \frac{S_{ij} - \min(S_i)}{\max(S_i) - \min(S_i)} \times 100 \quad (5)$$

Subsequently, using the global weights of the first-level indicators $W = (w_1, w_2, w_3, w_4)$ derived from AHP in the first stage, the final comprehensive integration utility score $U(X_j)$ of the scheme X_j is calculated (6):

$$U(X_j) = w_1 \cdot S_{1j}^{'} + w_2 \cdot S_{2j}^{'} + w_3 \cdot S_{3j}^{'} + w_4 \cdot S_{4j}^{'} \quad (6)$$

The final ranking is determined by sorting all candidate solutions in descending order according to their $U(X_j)$ values. This mechanism establishes a dynamic mathematical balance between computationally driven visual evaluation and semantically grounded cultural preservation.

4. Experimental Design, Implementation and In-depth Result Analysis

To evaluate the accuracy, efficiency, and practical applicability of the proposed AHP–AlexNet integrated decision-making model, this study selected the representative cultural element of traditional Chinese ceramics, Blue-and-White Porcelain, as the experimental case. A design optimisation experiment was subsequently conducted on a series of modern stationery and desktop office products developed around this cultural theme.

4.1. Experimental Environment Setup and Multi-Source Dataset Construction

The success of the experiment depended on constructing a high-quality visual dataset capable of effectively training the deep learning model. To achieve this, a hybrid data acquisition strategy combining physical image digitisation and web-based data collection was employed. The dataset comprised three primary sources: high-resolution images of Blue-and-White Porcelain artefacts obtained from publicly accessible museum digital collections, award-winning ceramic designs collected from recognised industrial design competitions, and AI-generated conceptual sketches of Blue-and-White Porcelain stationery created using carefully designed prompts. Following duplicate removal and data cleaning, a total of 6,000 representative image samples were retained for model development.

To establish reliable ground truth labels for supervised learning, an evaluation panel comprising postgraduate art and design students, experienced ceramic artisans, and general consumers was assembled. Using the Semantic Differential (SD) method, each image was evaluated on a 10-point bipolar scale ranging from "poor" to "exquisite", and the average score assigned by the evaluators was adopted as the corresponding aesthetic label. To enhance dataset diversity and improve model generalisation, data augmentation techniques, including random cropping, multi-angle rotation, colour perturbation, and Gaussian noise injection, were subsequently applied, expanding the dataset to 24,000 images [11]. The final dataset was then partitioned into training, validation, and testing subsets using a ratio of 8:1:1 (Fig. 3).

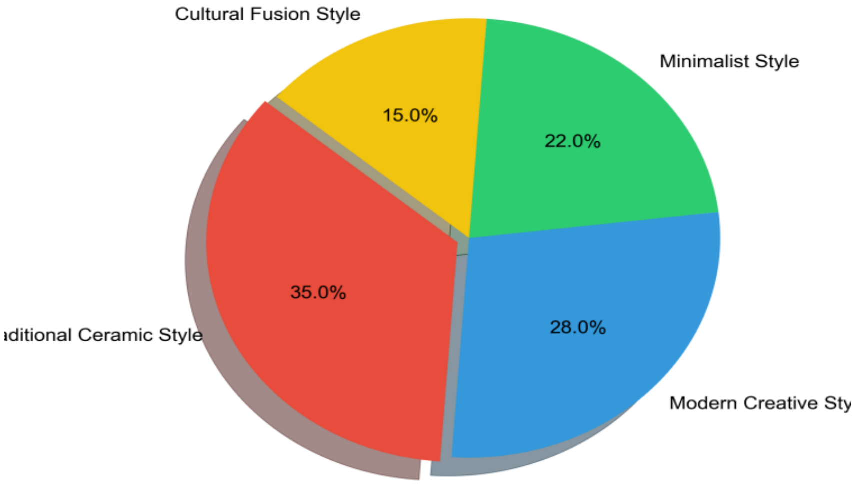

Fig.3: Composition Proportion Chart of the Ceramic Cultural and Creative Aesthetic Dataset

Hyperparameter Settings for Network Training: The model training process was conducted on a workstation equipped with an NVIDIA RTX 4090 GPU and implemented using the PyTorch framework. The Adam optimiser was employed, with the initial learning rate configured as 10-4. The Batch Size was set to 32, while the maximum number of training epochs was defined as 50. In addition, an early stopping strategy with a patience value of 10 was applied to continuously monitor validation set loss and reduce the possibility of model overfitting.

4.2. Quantitative Calculation and Consistency Analysis of the AHP Subjective Judgment Matrix

At the subjective evaluation stage of the framework, AHP questionnaires were administered to seven key experts to determine the global weight distribution of the first-level criterion layer. After collecting the expert assessments, the individual judgements were aggregated using the geometric mean approach to obtain the integrated first-level indicator judgement matrix, as presented in Table 1.

Table 1

Primary Indicator Judgment Matrix

Criterion Layer Comparison	Cultural Heritage and Inheritance (C_1)	Visual Aesthetics and Artistry (C_2)	Ergonomics and Practicality (C_3)	Innovation Potential and Marketability (C_4)
Cultural Heritage (C_1)	1	2	4	2
Visual Aesthetics (C_2)	1/2	1	2	1
Human-Machine Ergonomics (C_3)	1/4	1/2	1	1/3
Innovation Potential (C_4)	1/2	1	3	1

The judgement matrix was analysed using the Jacobi iterative approach in combination with the MATLAB toolbox, resulting in a maximum eigenvalue (λmax) of 4.0416. The consistency index was subsequently calculated as CI= (4.0416−4)/3=0.0138. For the fourth-order judgement matrix, the corresponding Random Consistency Index (RI) was confirmed as 0.89. Accordingly, the consistency ratio was determined as CR=CI/RI=0.0155<0.1, demonstrating that the judgement matrix satisfied the required logical consistency criterion. The subsequent calculation generated the global weight vector W for the four primary evaluation criteria: Cultural Heritage and Inheritance (w1=0.448), Visual Aesthetics and Artistry (w2=0.236), Human–Machine Ergonomics and Practicality (w3=0.089), and Innovation Potential and Marketability (w4=0.227). These results reveal the collective preference of the expert panel, indicating that cultural inheritance occupies the dominant position in the development and evaluation of cultural heritage-oriented creative products.

4.3. Performance Comparison of Deep Network Models and Discussion on Ablation Experiments

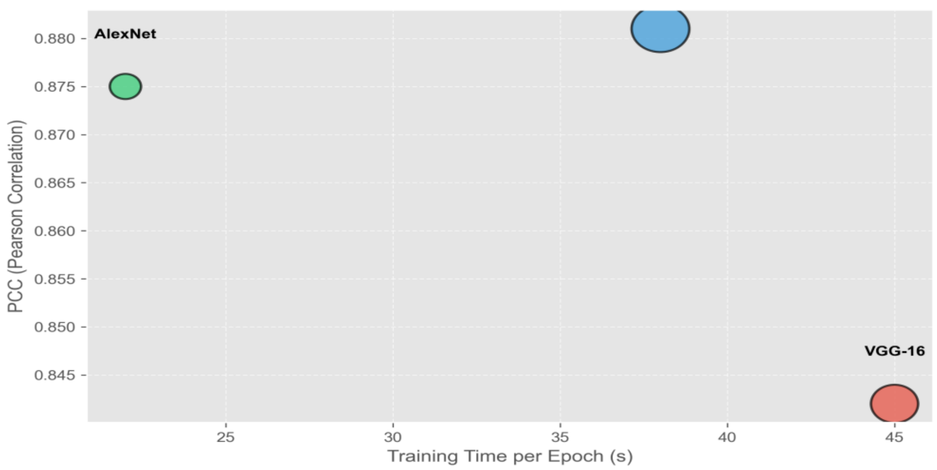

Fig.4: Bubble Chart Comparing the Comprehensive Performance and Parameter Quantity of Different CNN Models

During the model training stage, to assess the suitability of AlexNet for specialised design aesthetic evaluation tasks, this study conducted a comparative analysis involving two widely used benchmark architectures: VGG-16, which contains approximately 138 million parameters, and ResNet-50, which adopts a deep residual learning structure [9] (Fig. 4). All evaluated models were implemented using the same transfer learning framework and identical hyperparameter configurations to ensure comparability. Their performance was assessed based on MSE and PCC. The validation set comparison results of the three models are presented in Table 2 and Fig. 6.

Table 2

Performance Comparison Results of the Model on the Validation Set

Model Architecture	Parameter Magnitude (Approx.)	Training Duration (Epochs/s)	Validation Set MSE Loss	PCC Correlation Coefficient	Fitted Features and Evaluation Metrics
VGG-16	138 Million	185s	0.5058	0.842	The network is overly complex, the training process takes the longest time, and its generalization ability is slightly insufficient in the case of small sample sizes.
ResNet-50	25 Million	142s	0.4840	0.881	Residual connections accelerate convergence, resulting in the lowest MSE, but there is a very slight overfitting fluctuation.

AlexNet (fine-tuned version)	60 Million	65s	0.4912	0.875	Overall energy efficiency is the highest, achieving an excellent balance between feature extraction accuracy and time cost.

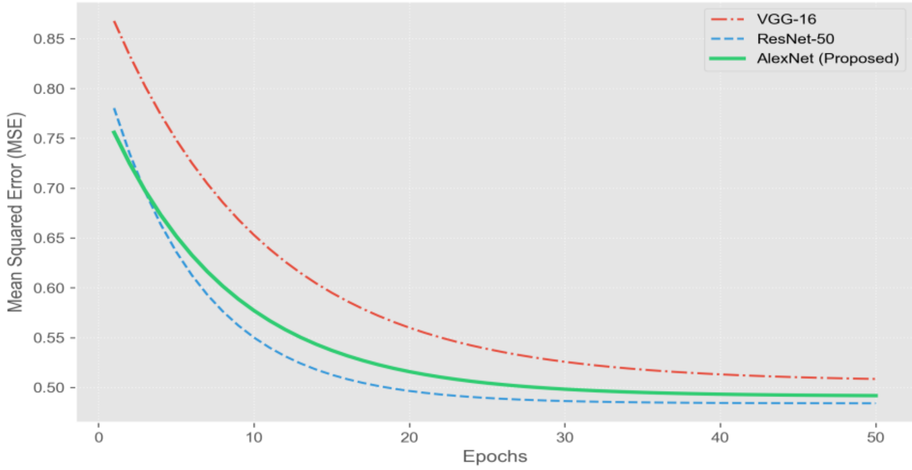

Fig.5: Convergence Curves of MSE Loss for AlexNet, ResNet-50, and VGG-16 on the Validation Set

The experimental findings demonstrate that, although the deeper ResNet-50 architecture achieved a marginally better MSE value (0.4840 compared with 0.4912), AlexNet, with approximately 60 million parameters, exhibited a clear advantage in computational efficiency. The training time required per epoch by AlexNet (65 s) was substantially lower than that of both ResNet-50 and VGG-16. More importantly, for ceramic design images characterised by irregular visual structures and intricate local textures, the moderate depth of AlexNet enables effective suppression of irrelevant background information while accurately extracting key aesthetic features, including form contours and colour harmony. This architecture also reduces the risk of dimensionality-related complexity and overfitting commonly associated with excessively deep networks. The strong agreement between AlexNet-generated aesthetic predictions and human evaluation scores (PCC = 0.875) provides reliable evidence supporting its application as an automated substitute for expert-based visual assessment [2; 13].

4.4. Verification of Decision-Making Effectiveness and Scheme Optimization

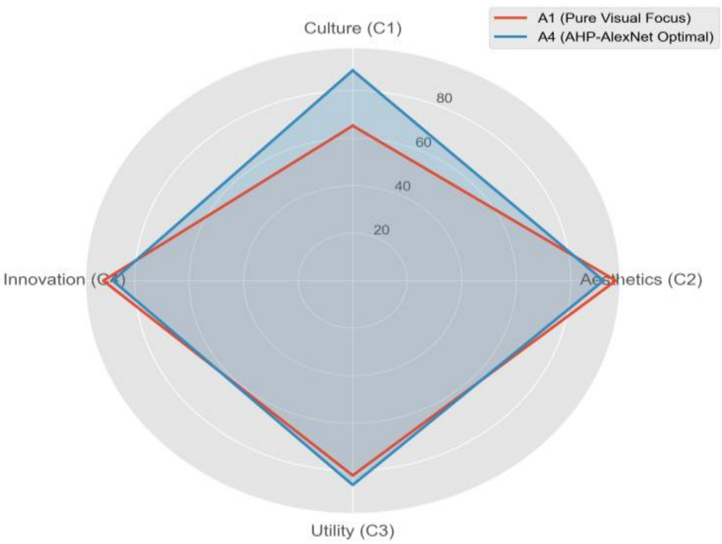

Fig.6: The Effectiveness Radar Evaluation Chart of 5 Candidate Solutions (A_1-A_5) in Four Dimensions

To complete the final decision-making process, this study selected five candidate schemes (labelled A1 to A5) from 100 preliminary designs generated through AIGC, ensuring that the selected samples represented diverse aesthetic scores predicted by AlexNet. These candidate designs were anonymised and subsequently evaluated by the expert panel based on non-visual criteria using a 100-point scale. To demonstrate the unique contribution of the proposed integrated framework, an ablation analysis was conducted to compare the ranking variations among three evaluation approaches: pure machine scoring, pure expert-based scoring, and AHP–AlexNet fusion scoring (Table 3, Fig. 7).

Table 3
Analysis of Rank Difference Abolition

Candidate Solution	Culture (S_1')	Practicality (S_3')	Innovation (S_4')	AHP Pure Manual Total Score	AlexNet Objective Aesthetic (S_2')	Integrated Total Score $U(X)$	Final Ranking and Decision Determination
A_1 (Geometric Deconstruction Pen Holder)	65.2	82.0	91.5	74.9 (4th Place)	96.5 (1st Place)	80.05	4th Place (Excellent in Pure Visual Aspect, but with Severe Cultural Gap)
A_2 (Traditional Replica Paperweight)	95.0	78.0	60.0	82.6 (1st Place)	72.4 (5th Place)	80.19	3rd Place (High Cultural Content, Lacking Modern Aesthetics)
A_3 (Magnetic Assembly Business Card Holder)	72.0	95.0	85.0	80.5 (3rd Place)	78.5 (4th Place)	78.52	5th Place (Pursuing Functionality, Lacking Artistic Appeal)
A_4 (Ink Wash Blue and White USB Drive)	88.5	86.0	88.0	87.8 (2nd Place)	92.0 (2nd Place)	88.99	1st Place (Optimal Balance: Cultural and Aesthetic Win-Win)
A_5 (Streamlined Multi-Functional Desktop Organizer)	80.0	80.0	85.0	81.3 (2nd Place)	89.2 (3rd Place)	83.29	2nd Place (Steady and Excellent Backup Solution)

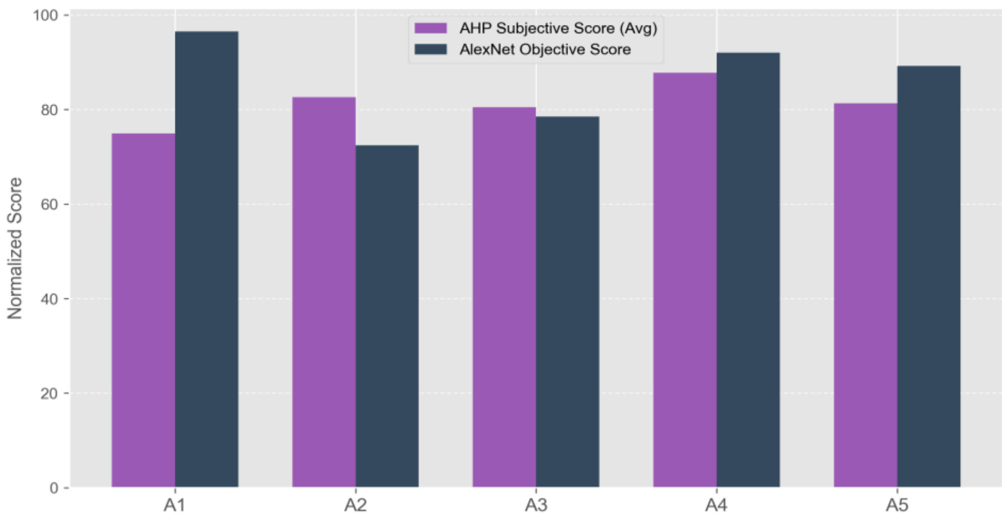

Fig.7: Comparison Chart of the Manual Scoring (Cultural/Practical/Innovative) of the Candidate Solutions by AHP and the Objective Aesthetic Score of AlexNet

A detailed examination of the results presented in Table 3 reveals several important findings. First, the limitations of relying exclusively on deep learning-based visual assessment become evident. For example, Scheme A1 incorporates highly deconstructive geometric elements and extensive negative space, characteristics that align strongly with the modern formal aesthetic patterns recognised by AlexNet, resulting in a high visual score of 96.5. However, the expert panel identified that the design weakened the essential "scroll pattern" semantic identity associated with Blue-and-White Porcelain, leading to a relatively low cultural evaluation score of 65.2 and consequently reducing its overall weighted ranking.

In contrast, an evaluation approach based solely on non-visual manual criteria would favour the highly conservative traditional replica paperweight design (A2) due to its exceptional cultural inheritance score. Nevertheless, AlexNet evaluation indicated that this design lacked contemporary aesthetic expression, receiving only 72.4 points in visual assessment. Among all evaluated alternatives, Scheme A4 achieved the most effective balance by integrating traditional cultural characteristics, modern visual appeal, and practical manufacturing considerations. The experimental findings confirm that the proposed AHP–AlexNet fusion framework effectively addresses the limitations of individual evaluation approaches. Specifically, it reduces the risk of cultural misinterpretation caused by AI models focusing solely on visual attractiveness while simultaneously alleviating the inconsistency and fatigue associated with manual assessment through automated computational analysis. Consequently, the proposed approach establishes a reliable quantitative decision-making mechanism for ceramic ICH creative product optimisation (Fig. 8).

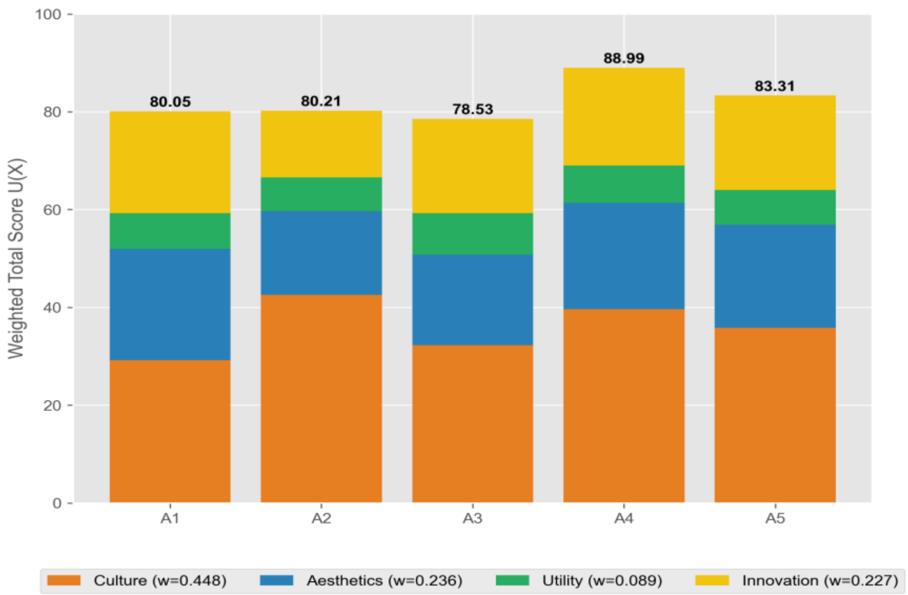

Fig.8: Stacked Bar Chart Showing the Overall Score Composition of the Candidate Scheme AHP-AlexNet's Comprehensive Performance

5. Discussion: Technological Boundaries and Industrial Implications

The effectiveness of the AHP–AlexNet fusion model in ceramic ICH creative product evaluation extends beyond numerical optimisation and data fitting. Its deeper contribution lies in establishing a theoretical and methodological understanding of the relationship between the objective analytical capability of machine algorithms and the human-centred emotional and cultural logic embedded within creative design.

5.1. The Crossing Mechanism of the "Semantic Gap" in Human-Machine Collaborative Decision-Making

A long-standing limitation of deep neural networks is their insufficient interpretability, as these models often function as "black boxes" that establish complex mappings between input image pixels and output predictions without providing explicit reasoning processes [15; 16]. This issue becomes particularly significant in cultural and creative product design, where designers require an understanding of the underlying factors contributing to high evaluation scores. By incorporating KE and the AHP framework, the proposed model integrates human prior knowledge into the evaluation process, thereby establishing meaningful constraints for deep learning-based assessment. Future developments of this collaborative framework may incorporate CAM techniques to further improve model interpretability. For instance, CAM can be applied to visualise image regions that receive greater attention from AlexNet when generating high aesthetic scores through attention heatmaps. If the model primarily focuses on ceramic form curves while overlooking culturally significant decorative patterns, designers can utilise the cultural evaluation criteria established by AHP to implement targeted modifications and corrective interventions. This multidimensional cross-validation approach reduces the gap between visual interpretation and cultural meaning, suggesting a future direction for industrial design in which humans define cultural boundaries and value principles, while AI performs optimisation across extensive design possibilities.

5.2. The Reformation of Intangible Cultural Heritage Digitization through Concurrent Design Paradigm

Empirical evidence indicates that the high efficiency achieved by the integrated decision-making framework in managing diverse and complex design alternatives has the potential to reshape the traditional supply chain structure of ICH craftsmanship [5]. Traditionally, the transition of ceramic cultural products from initial conceptual sketches to mould testing and refinement often requires months or even years, accompanied by substantial costs associated with repeated experimentation. In contrast, the framework developed in this study enables industrial systems to utilise AIGC engines for generating extensive collections of design variations at an accelerated pace. Within this large-scale design space, AlexNet functions as an initial intelligent screening mechanism, rapidly eliminating unsuitable alternatives characterised by poor colour coordination or disproportionate structural features. Subsequently, the remaining high-potential designs undergo a secondary and more detailed cultural evaluation through the AHP-based expert assessment framework. This approach transforms the conventional linear and sequential design process into a funnel-based paradigm comprising concurrent generation, intelligent screening, and targeted refinement. Beyond reducing inefficient manual design efforts, the proposed mechanism enables ICH elements to interact with emerging aesthetic trends, and market demands at a substantially accelerated rate. Consequently, traditional craftsmanship can achieve greater adaptability and appeal among younger consumers and international tourism markets while maintaining its cultural foundation [1; 5].

5.3. Cross-Category Adaptability and Dynamic Elasticity of Model Weights

The successful implementation of this framework in ceramic design highlights its considerable potential for application across diverse cultural and creative domains. By replacing the existing dataset with domain-specific samples, fine-tuning AlexNet parameters, and reconstructing the AHP judgement matrix according to the characteristics of different industries, the proposed architecture can be effectively extended to the innovative development of various ICH categories, including silk embroidery, wood carving, bamboo weaving, and metal engraving [3; 4]. Moreover, a significant advantage of the proposed model is its dynamic capability for weight adjustment. In practical commercial contexts, decision-makers can modify evaluation priorities according to the characteristics of target consumer segments. For example, in premium collection markets or museum-level cultural gift development, greater emphasis can be assigned to cultural inheritance and craftsmanship complexity within the AHP framework. Conversely, for fast-moving consumer products or markets driven by online trends and novelty seeking, higher importance can be allocated to innovation capability and the visual attractiveness assessed by AlexNet. This adaptive weighting mechanism transforms traditional KE from a static evaluation approach into a flexible and scientifically supported decision-making system capable of addressing diverse commercial scenarios throughout the product development lifecycle.

6. Conclusion

This study explores the integration of ICH preservation and modern creative design by addressing the limitations of subjective expert evaluation and the insufficient cultural understanding of individual computer vision models. By combining KE, AHP, and AlexNet, an intelligent evaluation framework with closed-loop decision capability was developed for ceramic ICH creative products. Theoretical analysis and experimental results demonstrate three key contributions. First, the AHP-based multidimensional evaluation system incorporating cultural heritage, functional practicality, and market potential ensures that innovative designs maintain alignment with traditional cultural values. Second, the transfer learning-based AlexNet model enables objective and efficient aesthetic assessment of complex artistic images while providing advantages in specialised design scenarios. Third, the AHP–AlexNet fusion mechanism effectively balances cultural authenticity and visual aesthetics by overcoming the limitations of purely data-driven approaches and subjective manual evaluation. Overall, the proposed framework provides a practical pathway for transforming ceramic ICH creative industries from experience-based decisions towards digital and intelligent evaluation. It also establishes a Human–AI collaborative paradigm for sustainable cultural heritage innovation in the AI era. Future studies may further enhance the framework by incorporating multimodal deep learning, image–text semantic analysis, and dynamic consumer feedback to support adaptive decision-making and continuous optimisation.

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