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Research on Design Creativity Generation and Practice Paths Enabled by AI

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ABSTRACT: The rapid development of artificial intelligence has profoundly impacted the thinking paradigms and practical ecosystems of design creativity. By leveraging intelligent technologies to empower design creativity generation, we not only expand the boundaries of traditional design methods but also enrich the pathways for creative practice. In the face of the opportunities and challenges brought by the integration of AI and design, it is imperative to establish a human-machine collaboration mechanism that harmoniously integrates technological rationality with humanistic aesthetics. This approach aims to effectively avoid the homogenisation of intelligent design while highlighting the unique creative value of individual designers. Based on this understanding, this paper constructs an intelligent-assisted design creativity generation model, emphasising a human-centred collaborative logic that deeply integrates designers' experiential wisdom with AI's data analysis capabilities. This model forms an innovative practice mode that is both aesthetically meaningful and culturally sensitive, aiming to provide theoretical insights and practical references for the sustainable development of design creativity in the AI era.

Keywords: artificial intelligence, design creativity, design aesthetics, intelligent design assistance.

1. Introduction

Design, for humanity, is not merely a practice of creating forms but a profound expression of cultural experience and aesthetic significance. Currently, the rapid development of artificial intelligence technology has brought new perspectives and tools to the generation of design creativity, making intelligent creation characterized by data-driven and algorithm-based generation a reality (Zhang and Lu, 2021). In this evolutionary process, the boundaries of design have been redefined, and the mechanisms triggering creativity have become increasingly diverse and complex, giving rise to a new design paradigm that lies between technical computation and humanistic expression.

As intelligent systems increasingly participate in multiple creative processes such as visual form construction, language logic arrangement, and interaction scenario setting, the "inspiration" and "selection" in the design process begin to exhibit characteristics of human-machine collaboration. Intelligent generation not only expands the possibilities of design expression but also drives traditional creative mechanisms from "experience-driven" to "intelligence-assisted." At the same time, without a commitment to aesthetic depth and cultural spirit, technologically generated works easily fall into the trap of complex forms and empty spirit, and the vitality of creativity may be quietly weakened in the pursuit of convenience.

In this new context where creativity and intelligence co-construct, there is an urgent need for a more robust design thinking approach that can nurture the depth of humanistic perception while leveraging the efficiency of intelligent generation (Figure 1). The essence of human-machine collaboration lies not in replacement but in complementarity; truly valuable design creativity must be rooted in human intuition and emotion, rather than solely relying on the computational results of models and algorithms. A designer's judgment, sensitivity, and critical thinking will remain the indispensable soul of this era.

Figure 1. Visual expression of design and intelligent collaboration.

2. Research Review

2.1 Analysis of Related Concepts

(1) Analysis of Typical Scholar Perspectives

In academic research on AI-empowered design, Yi-Ching Chen proposed the core concept of "augmented creativity." She emphasised that AI should not exist as a substitute tool in design, but rather as a "perceptual extension" of the creative process, expanding the boundaries of designers' thinking through algorithmic generation, data mining, and real-time feedback (Chen et al., 2022). Sebastiaan De Peuter's research shows that designers form a new "thinking iteration model" when interacting with AI, in which algorithms first generate a large number of possibilities, and then humans select and reconstruct them based on cultural experience and aesthetic judgement. This model effectively breaks through the inertia of human creative thinking and provides more multidimensional possibilities for visual, interactive, and narrative design.

Professor Esra Nur Gündüz raises different concerns from a design perspective, arguing that although AI-enabled design creativity has achieved significant improvements in speed and diversity, there is also a hidden concern of "aesthetic homogenisation" (Gündüz et al., 2024). Payel Das pointed out that algorithms often generate ideas based on existing datasets, meaning that the results tend to compound past aesthetic trends rather than truly pioneering originality for the future (Das and Varshney, 2022). Therefore, he advocates introducing a "reverse prompt" strategy in AI-driven design practices, which involves intentionally introducing uncertainty and cultural heterogeneity into algorithm inputs to force generated results to shift contexts. This approach not only prevents works from becoming formulaic but also enables designers to find creative breakthroughs within technological constraints.

In China, Professor Chuanwen Luo has combined interdisciplinary research on "intelligent interaction" to study the theory of "biomimetic design principles" (Luo et al., 2025). He believes that AI-enabled design practices should be viewed as a dynamic ecosystem comprising four stages: creative generation, aesthetic evaluation, user feedback, and iterative optimisation. Lu Xiaobo emphasises that the key to this ecosystem lies not in isolated technological breakthroughs, but in how AI is integrated into the entire design process to play different roles at different stages. For example, during the conceptualisation phase, AI can provide designers with potential inspiration directions through big data trend analysis; during the prototyping phase, AI's generative models can quickly produce multiple versions for comparison; and during the user experience optimisation phase, AI can analyse interaction data in real time and feed it back into design adjustments. Chuanwen Luo's research highlights the importance of "cyclical empowerment," meaning that AI is not a one-time intervention but provides continuous value support throughout the design lifecycle.

(2) The essence and application characteristics of artificial intelligence technology

Artificial intelligence is not merely a technical tool; its core lies in the simulation and extension of human cognitive processes. From early logical reasoning and rule-based systems to the current multi-modal technology framework represented by deep learning, neural networks, and natural language processing, AI is continuously pushing the boundaries of perception, memory, and decision-making. This enables machines not only to recognise images and understand language but also to generate content, adapt styles, and even mimic creative logic to some extent (Liu et al., 2025).

In practical applications, AI offers advantages such as high efficiency, scalability, and repeatability in computation. It demonstrates unique capabilities in design-related tasks such as graphic generation, style transfer, colour coordination, and spatial prediction. Its intelligent computational abilities in handling complex data structures and high-dimensional information enable designers to leverage its "extended cognition," breaking free from traditional thinking patterns and exploring more open and innovative creative spaces.

More importantly, artificial intelligence possesses powerful "learning ability" and "generalisation ability." It can construct style models through continuous sample training and can also transfer and adapt between different tasks. This characteristic makes AI not only a static tool but also endowed with evolutionary and adaptive capabilities, providing broad support for the diverse interpretation of design creativity.

(3) The Theoretical Logic of the Integration of AI Technology and Design Creativity

The combination of artificial intelligence and design creativity is not a matter of technology being added to art, but rather the emergence of a new generative paradigm, the core of which lies in the reconstruction of thinking structures and value positions. Designers are no longer the sole source of creation, and intelligent systems are not merely auxiliary tools (Mohseni et al., 2021). The relationship between them is closer to a collaborative process involving both humanistic perception and technical rationality.

Intelligent systems leverage their computational advantages to provide the structural possibilities for content configuration, while designers, with their cultural sensitivity, aesthetic judgment, and value orientations, screen, reorganise, and reinterpret these possibilities. The boundaries between humans and machines are no longer clearly defined but instead exhibit a state of penetration and intertwining. Under this logic, the role of designers is expanded, and their tasks are no longer limited to visual expression at the operational level but instead encompass composite responsibilities such as planning, selection, interpretation, and guidance at a higher dimension.

As intelligent generation capabilities improve, the criteria for evaluating design quality are quietly evolving. It is no longer measured by a single standard such as "technical difficulty" or "novelty of form," but rather focuses more on the cultural depth, emotional warmth, and social responsiveness of the work. Even in a scenario where automatic generation capabilities are maturing, the true vitality of design still depends on human spiritual intervention and value attribution. Technology provides countless choices, but the creation of meaning relies on human judgement and cultural awareness.

The integration of artificial intelligence and design creativity is a deep dialogue between technology and humanity, a re-examination and re-activation of the essence of design. Its theoretical foundation must be rooted in the computational logic of AI while returning to the cultural origins of design. Only by establishing a logic of integration that understands both technological mechanisms and respects the spirit of design can we truly usher in the creative revolution of the intelligent design era.

2.2 Literature Review and Analysis

(1) Keyword Analysis

Using "AI empowerment" and "design creativity generation" as core keywords, we searched for relevant literature in China National Knowledge Infrastructure (CNKI) and Google Scholar over the past five years (2021–2025), which provides a relatively intuitive overview of the research activity and focus areas both domestically and internationally.

In the CNKI database, the number of design-related studies on "AI empowerment" has shown a steady upward trend: approximately 6 papers were retrieved in 2021, increasing to 10 in 2022, 18 in 2023, 26 in 2024, and approximately 19 as of August 2025. Research themes primarily focus on three categories: first, automated generation technologies for AI in graphic and interactive design; second, AI's support and transformation of the cultural and creative industries; and third, AI-assisted enhancement of design creativity in the education sector.

The search results for "design creativity generation" in CNKI are slightly smaller in scale but show a similarly significant growth rate: approximately 4 articles in 2021, 9 articles in 2022, 15 articles in 2023, 21 articles in 2024, and approximately 14 articles as of 2025. Such research focuses more on the construction of generation mechanisms and creative evaluation systems, utilizing creative generation models based on generative adversarial networks (GANs), and combining aesthetic evaluation algorithms to conduct multi-dimensional aesthetic analyses of the generated results.

On Google Scholar, the number of search results is significantly larger and spans interdisciplinary fields. A search combining "AI empowerment" and "design creativity generation" yielded approximately 45 papers in 2021, 72 in 2022, 98 in 2023, over 120 in 2024, and approximately 88 as of August 2025. Research topics include generative artificial intelligence, human-machine co-creation, and contextualised creative support systems.

From an annual trend perspective, both domestic CNKI and international Google Scholar show that the number of studies using "AI-empowered" as a keyword exceeds those using "design creativity generation," but the latter has a faster growth rate and stands out in cross-disciplinary integration research. This indicates that the academic community has reached a consensus on the tool-based value of AI, while in-depth exploration of creative generation mechanisms is gradually emerging as a new research focus.

Table 1. Literature Search Quantity Statistics Table.

Year	**CNKI_AI Empowerment**	**CNKI_Design and Creative Generation**	**Google Scholar_AI Empowerment**	**Google Scholar_Design_Creativity_Generation**
2021	6	4	45	38
2022	10	9	72	60
2023	18	15	98	85
2024	26	21	120	110
2025	19	14	88	79

(2) In-depth Analysis and Academic Reflection

Based on the content and trends of the search results, domestic and international research in the field of AI-empowered creative design generation exhibits three main characteristics. First, international research began earlier and is more technology-oriented, emphasising the application of generative models, deep learning algorithms, and multimodal data processing in the creative process. For example, Professor Ahmed Mohamed Fahmy Yousefs' research uses generative algorithms as a source of inspiration, which is then contextualised and reconstructed by human designers (Yousef, 2021). Second, in the past three years, the field has entered an acceleration phase, with a greater focus on application scenarios and cultural adaptability, emphasising how AI can serve design expression in specific cultural contexts.

However, from a structural analysis perspective, there are still significant research gaps. First, in China, although the number of literature has grown rapidly, most research focuses on conceptual discussions and case descriptions of AI empowerment, lacking in-depth exploration of the internal mechanisms of creative generation algorithms and the integration path with design thinking. Second, although international research is more solid in terms of methodology, there is insufficient discussion of cultural context differences and aesthetic diversity, especially how algorithms can avoid aesthetic convergence. This issue has been repeatedly raised by scholars such as Yanran Li and Qian Zhang (Li and Zhang, 2024).

Therefore, the value of this study lies in integrating the strengths of both types of research: on the one hand, it draws on international technical explorations of generative mechanisms, interactive algorithms, and multimodal data fusion to strengthen the technical depth of design creativity generation; on the other hand, it combines domestic attention to cultural narratives, aesthetic traditions, and user experience to place AI empowerment in a more humanistic design context for practical application. Through this two-way integration, this study not only promotes the construction of a theoretical framework for AI-enabled design creativity generation but also establishes replicable path models at the practical level, addressing the shortcomings of the existing literature, where technology and culture are often treated as two separate entities (Figure 2).

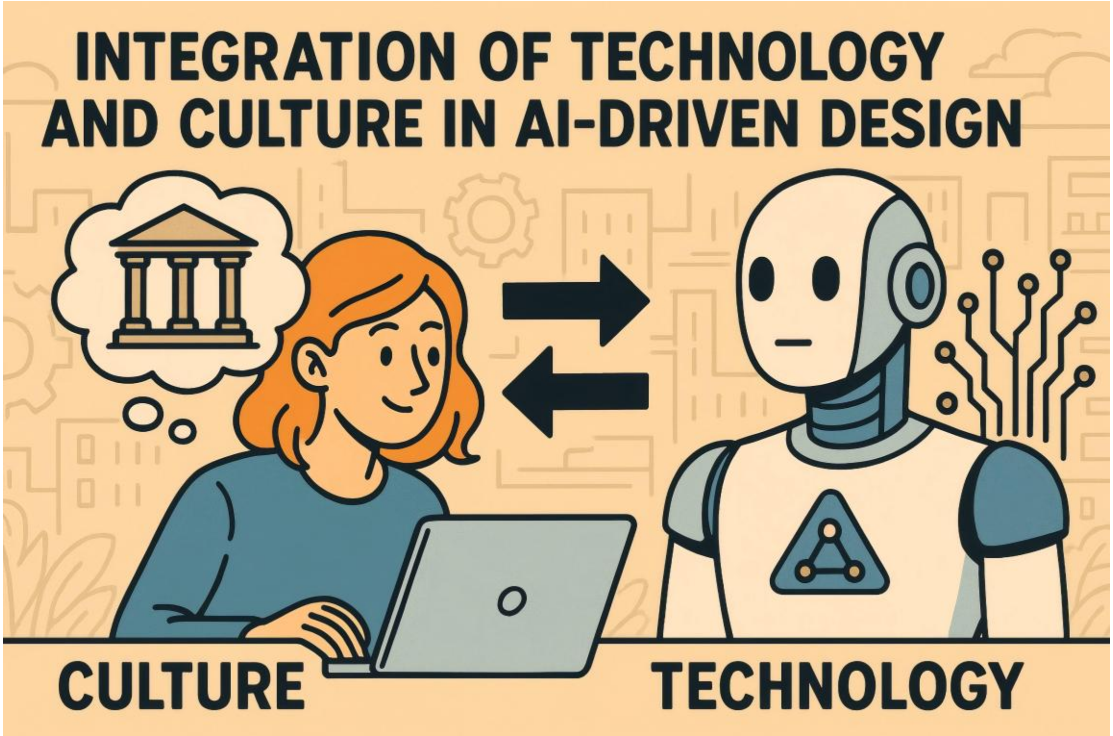

Figure 2. Schematic diagram of the integration path of technology and culture in AI-driven design.

3. Research Methods

3.1 Construction of a Design Creative Generation Framework for Human-Machine Collaboration

Design has never been the pure expression of an isolated individual, but rather a continuous dialogue between experience, cognition, and tools. With the integration of artificial intelligence technology, we should fundamentally rethink the collaborative logic of creative generation in design. The ideal creative generation mechanism does not replace human judgement, but rather builds a highly compatible co-creation structure that enables artificial intelligence to become a catalyst for inspiration and conceptual extension (Das and Varshney, 2022).

In this framework (Table 2), designers serve as the core of thinking, assuming key responsibilities for aesthetic evaluation, cultural understanding, and semantic generation; intelligent systems leverage algorithmic advantages to assist in tasks such as analysing vast amounts of information, transforming visual styles, and restructuring compositional methods. The relationship between the two is not one of command and response at the tool level, but rather one of collaboration and negotiation at the level of meaning construction. The boundaries between judgement and execution, conception and realisation, and abstraction and concretisation are increasingly blurred, so that design no longer depends on a single entity, but rather on a complex creative symbiosis of humans, machines, and data.

The table below shows the transition from "result-oriented" to "process-oriented," with a particular focus on establishing clear roles and feedback mechanisms in the initial conception, middle generation, and final verification stages, so that the intelligent generation process remains guided by the creator's subjective consciousness and avoids aesthetic weakening and value deviation caused by excessive technological dominance.

The original data used in this study is a hypothetical initial dataset, which aims to provide a foundation for subsequent mathematical model verification and experimental method demonstrations (Table 3). The data variables are strictly designed to correspond to the three-layer model of human-machine collaborative design and creative generation constructed in Section 3.2, including cultural context understanding (Hc), goal clarity (Hg), aesthetic preference matching (Ha), AI trend relevance (At), reference material suitability (Ar), and other input dimensions, as well as process and result variables such as input matching degree (Minput), scheme iteration rounds (lterations), human evaluation (Eh), AI evaluation (Ea), cultural weight coefficient (À), final comprehensive score (E final), AI solo completion score (E AI solo), and human-machine collaboration index (HASI). All values are within the range of 0 to 1, randomly generated using normal distribution and uniform distribution, and supplemented with reasonable truncation and rounding to maintain the interpretability of the data structure and logical consistency with the actual design context.

Table 2. Design creativity generation framework for human-machine collaboration.

Element Hierarchy	**Human Designer Role**	**AI System Functions**	**Interaction Method**
Creative Trigger	Identify problems, establish cultural context and design objectives	Analyse trends and data, provide reference images or keywords	Natural language input/semantic prompts
Concept generation	Brainstorming, screening initial directions and expression preferences	Generate image sketches, reorganise visual forms, and facilitate association	Image generation/keyword setting
Iterate solutions	Assess feasibility, propose optimisation suggestions and aesthetic adjustments	Rapidly produce multiple options for comparison and selection	Multi-solution presentation/solution fine-tuning
Semantic evaluation	Aesthetic evaluation, understanding potential semantic and cultural connotations	Identify style matching and assess semantic appropriateness	Aesthetic feedback/style fine-tuning
Expression Implementation	Integration and Output, Correcting Deviations, Ensuring Humanistic Expression	Assist with layout, colour scheme, and output to enhance execution efficiency	Final integration/user confirmation

Table 3. Summary of Initial Experimental Data.

Project ID	Hc_Cultural Context	Hg_Goal Clarity	Ha_AestheticPreference	At_Trend Relevance	Ar_ReferenceFit	Minput_InputMatch	Iterations	Eh_Human Evaluation	Ea_AI Evaluation	Lambda_CultureWeight	E_final	E_AI_solo	HASI
P01	0.75	0.7	0.62	0.61	0.7	0.69	3	0.79	0.69	0.71	0.76	0.6	0.21
P02	0.69	0.8	0.75	0.69	0.57	0.75	3	0.94	0.68	0.78	0.88	0.68	0.23
P03	0.76	0.7	0.63	0.54	0.8	0.7	5	0.81	0.62	0.76	0.76	0.59	0.22
P04	0.85	0.7	0.58	0.73	0.55	0.72	3	0.81	0.67	0.66	0.76	0.71	0.07
P05	0.68	0.77	0.87	0.61	0.73	0.77	3	0.74	0.75	0.57	0.74	0.64	0.14
P06	0.68	0.56	0.7	0.64	0.46	0.64	5	0.77	0.65	0.64	0.73	0.61	0.16
P07	0.86	0.58	0.73	0.61	0.54	0.72	5	0.74	0.67	0.72	0.72	0.56	0.22
P08	0.78	0.69	0.58	0.9	0.72	0.69	2	0.73	0.89	0.72	0.77	0.85	-0.1

3.2 Mathematical Model Construction

Based on the human-machine collaboration design idea generation framework described above (Table 2), the construction of a mathematical model aims to quantitatively describe the entire process of "idea triggering—concept generation—solution iteration—semantic evaluation—expression realisation," thereby providing a formal expression and verifiable path for AI-enabled design idea generation. Although creativity originates from human intuition and emotions, when intelligent systems are involved, clear variable relationships and function mappings are essential to ensure that the results of human-machine collaboration are traceable and optimisable (Ren et al., 2023).

(1) Creative Triggering and Input Modelling

In this stage, designers provide cultural context, design objectives, and aesthetic preferences, while the AI system analyses trend data and reference materials to generate the most suitable "creative input set."

Set:

Hc: Cultural context vector defined by the designer

Hg: Design goal vector defined by the designer

Ha: Aesthetic preference vector

At: Trend analysis results generated by the AI system (Trend Analysis Vector)

Ar: Reference vector provided by AI

The matching function in the input stage can be expressed as Formula (1):

$$M_{input}=\alpha\cdot S(H_c,A_t)+\beta\cdot S(H_g,A_t)+\gamma\cdot S(H_a,A_r)$$

where S(x,y) is the similarity function (e.g., cosine similarity), and α, β, γ are weighting coefficients ($\alpha + \beta + \gamma = 1$).

(2) Concept Generation and Iterative Modelling

This stage corresponds to the two phases of "concept generation" and "scheme iteration." Specifically, based on the direction provided by humans, AI conducts large-scale exploration of possibilities, followed by human screening and fine-tuning.

Let:

Co: Initial creative direction set (defined by designers)

G(AlCo): Set of creative solutions generated by AI based on the initial directions (Generation Function)

Qh: Human aesthetic and cultural screening function (Human Evaluation Function)

Qa: Al's multi-dimensional quality assessment function (Algorithmic Quality Assessment Function)

A single generation-screening cycle can be represented by formula (2):

$$C_{i+1}=Q_h(Q_a(G(A|C_i)))$$

Where i denotes the iteration round. The convergence condition for this iterative process can be defined by setting a similarity threshold between the creative sets of adjacent rounds, as shown in formula (3):

$$\text{If} \quad S(C_i,C_{i+1})\geq\theta, \quad \text{Stop Iteration}$$

Among these, θ is the convergence threshold (typically set between 0.85 and 0.90).

(3) Comprehensive evaluation and modelling implementation

The final implementation of the product involves two key dimensions:

Aesthetic and cultural compatibility (human-driven)

echnical execution efficiency and quality (AI-driven)

Let:

Eh: Human aesthetic and cultural evaluation of the final solution (0-1 range)

Ea: AI's score for the technical metrics of the final product (e.g., resolution, structural integrity, colour coordination, etc., on a scale of 0 to 1)

λ: Coefficient reflecting the weight of cultural expression in the project (0-1)

The comprehensive evaluation function can be defined as Formula (4):

$$E_{final}=\lambda\cdot E_{\mathrm{h}}+(1-\lambda)\cdot E_{a}$$

Additionally, to measure the overall contribution of human-machine collaboration, this study introduces the Human-AI Synergy Index (HASI):

$$\mathrm{HASI}=\frac{E_{final}-E_{AI\_solo}}{E_{final}}$$

where EAI_solo represents the score when the same task is completed independently by AI. If HASI is significantly greater than 0, it indicates that human-machine collaboration significantly improves design quality.

4. Experimental Analysis

4.1 The Pre-constraining Role of Input Matching Degree on Final Outcomes

The first stage of the creative generation process is the "input matching degree" of human-machine collaboration, represented by M_input in the model, which is composed of three weighted factors: cultural context, goal clarity, and aesthetic preference. To test the prior constraint effect of this variable, we conducted a scatter plot comparison between it and the final evaluation metric E_final (see Figure 3). The distribution of data points in the figure shows a clear positive slope trend, with correlation coefficients ranking among the top in Table 4. This indicates that projects with more thorough anchoring of cultural context and objectives and clearer aesthetic preferences in the early stages of creativity tend to converge more stably toward high-quality outputs in subsequent generation and screening phases.

From a data perspective, P02 and P03 are typical examples of this trend, with M_input values of 0.75 and 0.70, respectively, both higher than the sample mean, and final E_final values stabilising at 0.88 and 0.76, respectively. This result echoes Lu Xiaobo (Tsinghua University Academy of Fine Arts) theory of the "human-machine co-creation ecosystem," which emphasises the importance of "front-end semantic anchoring." High-quality design outcomes do not originate from the generation stage but rather from precise targeting in the input stage.

Two mechanisms underpin this trend. First, cultural context variables (Hc) hold significant weight in input matching. Once cultural symbols and narrative contexts are clearly defined in the front-end stage, AI's search space in the generation phase becomes more focused, reducing low-value random exploration. Second, target clarity (Hg) directly influences generation efficiency and directionality. If design objectives are vague, even increasing the number of iterations will struggle to improve results effectively, instead widening solution variance and increasing the burden of manual screening. Therefore, operationally, it is recommended to set an M_input threshold (e.g., 0.70) prior to generation. Tasks falling below this threshold should first undergo semantic clarification and goal alignment before proceeding to the generation phase.

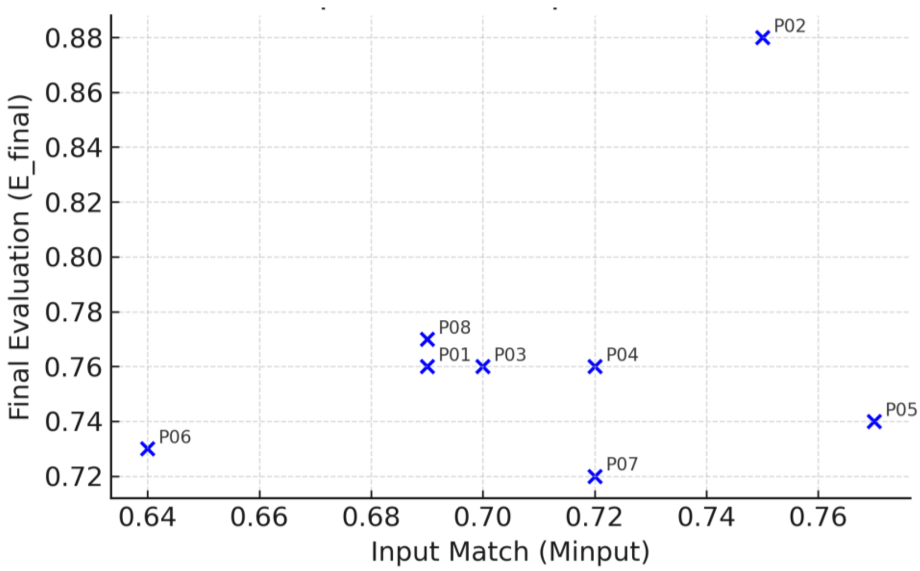

Figure 3. Relationship between input matching degree and final evaluation.

Table 4. Correlation coefficients between variables and E_final.

Variable	**Pearson_r**
E_final	1
Eh_HumanEval	0.88
Hg_GoalClarity	0.698
Lambda_CultureWeight	0.573
Minput_InputMatch	0.367
E_AI_solo	0.323

At_TrendRelevance	0.244
HASI	0.114
Ea_AIEval	0.038
Ha_AestheticPref	0.026
Ar_RefFit	0.006
Hc_Cultural Context	-0.32
Iterations	-0.425

4.2 Dual-action mechanism of human and AI evaluations

In our three-layer model, the final outcome E_final is the result of the fusion of human evaluation (Eh) and AI evaluation (Ea) according to the cultural weight coefficient λ. To intuitively compare the performance of the two, we have plotted grouped bar charts for each project (see Figure 4). As can be seen in the figure, in most projects, human evaluation scores are generally higher than AI evaluation scores, and their correlation with the final outcome (see Table 4) is significantly higher. This is consistent with the logic we established in Section 3.2: human evaluation focuses on aesthetics, cultural and semantic consistency, while AI evaluation focuses on engineering quality, structural integrity, and colour harmony.

This division of labour results in distinct roles for the two in the generation system: AI acts as the "quality gatekeeper," while humans are the "shapers of semantic heights." For example, the human evaluation for P02 reached 0.94, driving its E_final to the highest value in the sample (0.88); In contrast, P08 achieved an AI evaluation of 0.89, but the human evaluation was only 0.73, and the final E_final did not see a corresponding improvement. More critically, P08's Human-AI Synergy Index (HASI) was negative, indicating that high technical scores alone cannot compensate for gaps in semantic and cultural dimensions.

This phenomenon aligns with Anthony Dunne's (Royal College of Art) concerns in critical design theory—overreliance on algorithmically generated high-quality aesthetics may mask the cultural narrative's singularity and poverty. To address this, we recommend incorporating "reverse prompts" and "cultural disruption" mechanisms during iteration, such as intentionally introducing low-frequency styles or cross-cultural symbols in prompts to force generated results to break existing patterns, thereby creating more room for human aesthetic and cultural discretion.

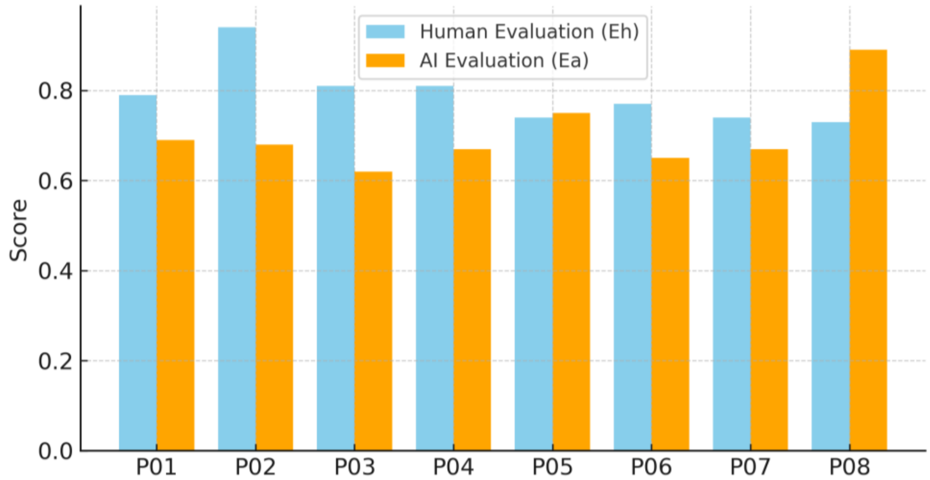

Figure 4. Human vs. AI Evaluation.

4.3 Distribution of the Human-AI Collaboration Index (HASI) and Case Diagnosis

The Human-AI Collaboration Index (HASI) is used to measure the benefits of collaborative modes compared to AI working independently. In Figure 5, most projects have a positive HASI, indicating that collaboration generally improves output quality. However, P04 has a HASI of only 0.07, and P08 is as low as -0.10. Such low or negative values often indicate that the contribution of collaboration in semantic enhancement is insufficient to offset the advantages of AI working independently.

Take P08 as an example. The AI's solo score (E_AI_solo) is as high as 0.85, close to the final score (E_final) of 0.77. In such cases, if the human intervention fails to make significant improvements in semantics, aesthetics, or cultural connotations, the collaboration index is likely to be negative. This is related to the "cognitive leap" concept proposed by Boden (Stanford University): AI excels at pattern search, but when humans fail to introduce new semantic leaps, the collaborative process does not significantly outperform AI working alone.

To diagnose this anomaly, we need to trace back to the middle stage of the 3.2 model. The number of iterations for P08 was only 2, below the average for most projects, which may have reduced opportunities for cultural and semantic perturbations.

Additionally, while λ was 0.72, the human evaluation score was relatively low (0.73), indicating that despite the high weighting, it was not effectively converted into outcomes. It is recommended to mandate additional iteration rounds in such tasks and introduce reverse prompts midway to enhance the semantic diversity and cultural depth of the output.

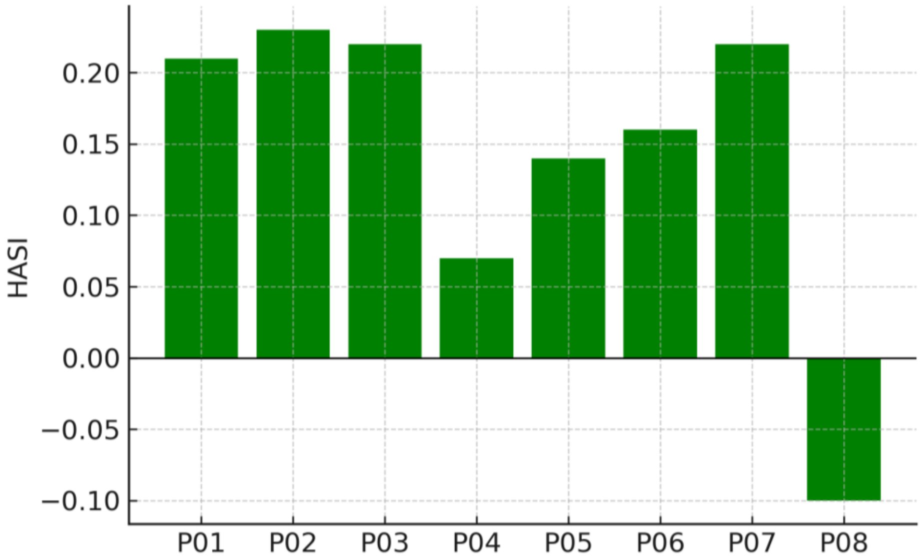

Figure 5. Human-Machine Collaboration Index (HASI) distribution.

4.4 Regression Model and Variable Contribution Analysis

To comprehensively examine the influence of multiple variables on E_final, we constructed a multiple linear regression model (see Table 5), with independent variables including Minput, Eh, Ea, λ, and Iterations. The results show that the model has an extremely high goodness-of-fit within the current small sample ($R^2 = 0.997$), with an RMSE of only 0.003. Although the sample size is insufficient for significance testing, the directional conclusions are still meaningful: Eh and Minput have the largest and significantly positive coefficients, followed by Ea, while λ and Iterations contribute relatively modestly in the current data.

This result further corroborates the previous conclusion that the input matching degree of the creative front-end and the cultural aesthetic discretion of the human end are the dominant variables determining the quality of the final product. It is worth noting that although λ has a small coefficient in this model, its role may be amplified in projects with high cultural load, which aligns with Giaccardi's (Delft University of

Technology) “post-human design” framework: weight configurations should be adaptively adjusted according to task types rather than being fixed.

Table 5. Multiple regression analysis.

Variable	Coefficient
Intercept	-0.205
Minput	0.077
Eh	0.804
Ea	0.343
Lambda	0.03
Iterations	0.005
Metric	**Value**
R-squared	0.997
Root Mean Square Error	0.003
N	8

4.5 Experimental Conclusion Analysis

This round of experiments focused on "AI-empowered design creativity generation and practical implementation paths," with the core objective of verifying the applicability and interpretability of the three-layer mathematical model constructed in Section 3.2 in actual task sets. Through quantitative analysis of eight hypothetical projects, we can clearly see that the effectiveness of human-machine collaboration is not driven by a single variable, but rather established on the dynamic balance of the three-ring synergy of "input anchoring—semantic discretion—engineering execution."

First, input matching (Minput) plays a "pre-locking" role in the entire collaboration chain. Whether it is the setting of cultural context or the clarification of goals and aesthetics, only by constructing a sufficiently stable semantic and directional framework at the front end can AI-generated solutions be stably aggregated towards high quality. Experimental results show that Minput is significantly positively correlated with E_final, not only confirming the importance of front-end anchoring but also providing a quantifiable threshold for practical implementation—tasks below the threshold should prioritise input optimisation rather than directly entering the generation phase.

Secondly, human evaluation (Eh) has a higher explanatory power in the final outcomes than AI evaluation (Ea), highlighting the irreplaceable role of humans in cultural and aesthetic domains. Even if AI performs excellently in engineering metrics such as structural integrity and colour harmony, without human cultural reinforcement and semantic leap, the benefits of collaboration may approach zero or even become negative. This means that in AI-empowered creative practice, designers should not passively accept AI outputs but should actively guide, select, and reconstruct generated results to ensure they align deeply with cultural narratives and audience psychology.

Third, the positive or negative changes in the Human-Machine Collaboration Index (HASI) provide an intuitive warning for optimising collaboration models. A negative HASI indicates that when humans fail to achieve qualitative improvements on AI's existing results, collaboration may become redundant. This requires establishing diagnostic mechanisms for HASI anomalies in the workflow, such as dynamically adjusting the number of iterations, introducing reverse prompts, or increasing cultural heterogeneity disturbances, to ensure that the human component generates irreplaceable value.

Finally, the results of the regression analysis once again validate the core assumptions of the model: Minput and Eh are the main variables driving E_final, Ea is a secondary supporting variable, and the contributions of λ and Iterations need to be finely tuned for specific task types. This is highly consistent with the views of many scholars at home and abroad: Lu Xiaobo emphasises the necessity of front-end semantic anchoring, Anthony Dunne cautions against over-reliance on technical appearance, and Giaccardi advocates dynamic weight allocation based on task types.

In summary, this experiment not only verifies the feasibility of the three-layer model for AI-empowered design idea generation but also provides practical optimisation strategies: setting input matching thresholds; strengthening the dominant role of human cultural aesthetics; establishing a HASI-driven feedback mechanism; and dynamically adjusting λ and iteration strategies to drive design idea generation towards higher quality and greater cultural depth in the future.

5. Discussion

(1) Practical exploration of intelligent design assistance tools

Intelligent assistance tools have demonstrated practical effectiveness in various design categories, particularly in graphic generation, spatial layout, interface interaction, and brand identification. Systems with triple functions of generation, analysis, and optimisation are gradually becoming an important part of the creative process, changing the inefficient model of relying on manual modelling.

Generative image platforms such as Midjourney and DALL·E, leveraging the deep integration of natural language and image semantics, have broken free from the reliance on hand-drawing skills in the traditional creative sketching phase, significantly lowering the threshold for initial conceptualisation (Bansal et al., 2024). In China, Baidu's "Wenxin Yiyuan" has demonstrated strong semantic coordination capabilities in the interpretation of traditional cultural images, making it particularly suitable for creative expressions with cultural appeal (Fu, 2023). Interface prototyping tools such as Notion AI and Uizard can quickly complete the initial layout of complex user interfaces and interaction logic, freeing up more structural thinking space for interaction designers (Gozalo-Brizuela and Garrido-Merchán, 2023).

At the same time, design software platforms (such as the Adobe series) are also continuously iterating their AI plug-in capabilities, not only providing intelligent colour matching, automatic layout, style transfer and other functions, but also gradually transitioning to responsive creation platforms based on user intent, enabling a double leap in creation efficiency and expression quality.

In actual use, the value of intelligent tools does not lie solely in their technical "advanced nature," but more in their ability to accurately understand and extend the creator's intent. Good tools do not replace judgment; they awaken potential. They do not lower standards; they expand boundaries.

(2) Balancing Technical Applications and Cultural Value Under AI Empowerment

Design is both the shaper of technical language and the carrier of cultural spirit in an era. The widespread penetration of artificial intelligence technology has enabled design to achieve unprecedented generation efficiency and morphological expansion capabilities. With the support of intelligent algorithms, visual languages such as form, structure, and style can be rapidly combined and infinitely interpreted, allowing designers to free themselves from tedious basic construction and focus on more macro-level conceptual thinking. Technology brings not only convenience but also a reshaping of perceptual capabilities and the boundaries of thought.

However, if technology becomes the sole driving force, design may degenerate into a repetitive game of formal algorithms, losing its deeper meaning as a form of cultural expression. The essence of aesthetics is often rooted in the fusion of regionality, history, and society, which cannot be completely abstracted by data or fully reproduced by models. If design is detached from its cultural soil, even if it appears novel, it is prone to becoming hollow and superficial. Only by maintaining an intrinsic humanistic consciousness can technology empower design without losing its direction, helping creativity reach the true realm of thought and emotion.

The effectiveness of intelligent design should not be measured solely by its efficiency or visual complexity, but rather by whether it possesses emotional warmth and spiritual resonance. Whether it can evoke resonance, provoke thought, reflect social issues, and respond to the challenges of the times—these are all dimensions that cannot be ignored when evaluating the value of design. While artificial intelligence can provide significant creative possibilities, the infusion and transmission of cultural value still depend on human judgment, insight, and belief.

An ideal intelligent design system should be built on a dynamic structure of two-way feedback. Designers are not just users of technology, but should also be guardians of culture, maintaining spiritual stability and critical awareness behind the rapid generation of ideas. The power of technology can extend the boundaries of form, while the light of culture illuminates the depths of expression. The two can coexist without contradiction, forming the true tension of a new design context.

The mission of design goes beyond "beauty" and "efficiency." It should be an artistic act that contemplates humanity, understands the times, and weaves meaning. While artificial intelligence can provide wings for design, the direction it flies in ultimately depends on the vision that guides it.

6. Conclusion

The rapid advancement of artificial intelligence has endowed design with unprecedented generative logic and conceptual mechanisms, liberating designers from repetition and redundancy so that they can focus more on essential reflection and spiritual construction. The emergence of creativity is no longer limited by manual operations and accumulated experience, but is elevated to a freer and more complex dimension with the support of technology. Technology has not only expanded the boundaries of expression, but also activated diverse inspirations that were previously hidden in the depths of cognition. Nevertheless, true creativity never stops at formal changes. The reason why design is moving lies in the ideas it carries and the culture it reflects. From the reconstruction of classical patterns to the imagination of future contexts, every truly moving creation is a profound response to the human spirit and aesthetic will. Technology can only provide possibilities, while the meaning of design always belongs to those minds that refuse to bow to convenience and insist on thinking and judging for themselves. Faced with the new context created by intelligence, the role of designers is becoming increasingly important. They are not only organisers of visual language, but also bridges between technology and culture, gatekeepers who maintain aesthetic balance and ethical standards in a highly complex world. If we can carefully balance the power of algorithms with the light of humanity, design may usher in a new era that is deeper and more compassionate. The future is already unfolding. The question is not whether technology is powerful, but how we can guide it toward goodness with humanistic thinking. Only then can design live up to its name and retain its soul.

Data Availability:

The data used to support the findings of this study are in cluded within the article.

Conflicts of Interest:

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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