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KNOWLEDGE-AUGMENTED AGENTIC SYSTEMS FOR TRADITIONAL COSTUME PATTERN DESIGN

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ABSTRACT
Generative AI has accelerated visual design workflows, yet it remains limited in domains that require cultural sensitivity, compositional precision, and production feasibility. Traditional costume pattern design exemplifies these challenges, demanding alignment with symbolic meaning, design conventions, and craft constraints.

We present a knowledge-augmented agentic system tailored for professional design tasks. Powered by a large language model, the system follows a closed loop of perception, retrieval, generation, reflection, and revision. It integrates tools such as pattern-aware foreground segmentation, motif-level inpainting, symmetry-based layout editing, and style-guided color adjustment to support culturally and structurally grounded outputs. The system leverages a structured retrieval module, including 504 design rules, 781 expert cases, and a curated style bank of 20 annotated reference images. Retrieved knowledge is translated into actionable design constraints, guiding iterative refinement throughout the process.

This approach enables deeper integration of generative AI with traditional design practice, offering a system capable of producing culturally coherent, visually balanced, and production-ready costume patterns. The approach provides a viable pathway for integrating cultural context, aesthetic principles, and craft constraints into generative workflows.

A demo is also available at http://122.51.124.104:8888/.

Keywords: AI in Design, Image Generation, Agentic System, Traditional Costume Pattern Design

1 INTRODUCTION

Design studies have long employed symbols, patterns, and text as mediums to express identity and meaning, with traditional costume patterns serving as a representative domain that combines aesthetic value and technical norms[1, 2]. For humans, these patterns are not merely decorative elements but a rich visual language, encoding historical narratives, social status, and collective identity. In recent years, generative artificial intelligence has rapidly permeated design practice, reshaping creative workflows and significantly reducing prototyping costs[3, 4]. From early generative adversarial networks to diffusion models, systems like Midjourney [5] and Stable Diffusion [6] have continually elevated the upper limits of generation quality. Conversational image-generation models, such as GPT-Image-1 [7] and Gemini-2.5-flash-image-preview [8], have further lowered barriers to entry through multimodal interaction, enabling non-experts to quickly create and iterate images.

However, when tasks shift from "image generation" to real-world traditional costume patterns design, which requires adherence to professional norms, existing models still exhibit limitations[9, 10, 11]. Firstly, when generating traditional costume patterns, the model often exhibits ambiguous composition hierarchy and a lack of clear primary-secondary logic; this issue is particularly acute with cultural semantics, where pattern symbols are incorrectly appropriated or misplaced, which weakens their original cultural semantics; the proportion between decorative patterns and negative space is imbalanced, resulting in insufficient visual tension or excessive overcrowding; at the same time, the color system lacks overall control, making it difficult to maintain visual unity and harmony of the patterns[12]. This failure stems from a fundamental disconnect: current generative models perceive patterns as statistical arrangements of pixels or tokens, lacking a deep, grounded understanding of their embedded cultural context. Additionally, creating traditional costume patterns involves a multi-step workflow, including understanding cultural contexts, material separation, pattern abstraction, color system exploration, and final output. The entire process demands constant designer engagement to coordinate and adjust various tools, often requiring frequent switching between AI platforms and repeated prompt-based trial-and-error[13]. This workflow is cumbersome and places substantial demands on the designer's expertise with AI technologies. Existing attempts, including prompt engineering [14, 15], retrieval augmentation [16, 17], and lightweight fine-tuning techniques like LoRA [18], DreamBooth [19], and textual inversion [20], offer assistance in specific styles. However, they lack explicit modeling of design experience and cannot dynamically adjust their strategies to accommodate different user requirements. As a result, they are often user-unfriendly and do not consistently ensure professional compliance.

To address these bottlenecks, we propose a **knowledge-augmented agentic system** specifically designed for traditional costume pattern creation. Powered by a large language model, the system can dynamically select and utilize various tools based on user requirements, and further refine its generated images through self-reflection. Complementing the agentic system is a locally curated knowledge base tailored for traditional custom design, comprising three key components: (1) a costume pattern design norm base, encoding **504** retrievable rules covering pattern vocabulary, compositional hierarchies, arrangement logic, color principles, and craft constraints; (2) a design experience and knowledge base containing **781** samples, which consolidates heuristic insights, aesthetic paradigms, and actionable principles from textbooks and practical cases; and (3) a reference style bank of **20** hand-curated images with descriptive captions, providing classic examples for style guidance during generation.

To demonstrate the advantages of our approach, we have evaluated our system alongside **4 flagship generative models** across **10 representative design tasks**, encompassing pattern generation, composition layout, and color exploration. These tasks are aligned with real-world traditional costume pattern creation workflows. Two professional designers participated in a 5-point Likert scale evaluation, assessing five key dimensions: cultural relevance, pattern accuracy, aesthetics, perceived usability, and scene adaptability. The results indicate that our agentic system consistently outperforms baseline models across all assessed dimensions, particularly in cultural relevance and pattern accuracy. Case studies further highlight its robust capability to adaptively leverage different tools for diverse design scenarios, while effectively integrating retrieved knowledge as executable constraints during both generation and editing.

Overall, our contributions are threefold:

- We present **a comprehensive knowledge base** specifically curated for traditional costume pattern design, incorporating structured and retrievable professional design rules to enhance the normative quality of generation.
- We introduce **a novel agentic system** that dynamically orchestrates tool selection and adaptation based on user input, equipped with self-reflection and refinement capabilities.
- We establish **a practice-oriented benchmark** for systematically evaluating AI performance in traditional costume pattern design.

2 RELATED WORKS

2.1 AI in design

Artificial intelligence (AI) is profoundly transforming the art and design industry[21, 22]. Recent advances, from Generative Adversarial Networks (GANs) [23] to diffusion models [24], have significantly improved the efficiency and controllability of AI-generated images. Building on this, industrial-grade systems such as DALL·E 2 [25] and Midjourney [5] have further enhanced both user experiences and image quality. More currently, flagship models, such as OpenAI's GPT-Image-1 [7] and Google's Gemini-2.5-flash-image-preview [8], demonstrate exceptional image generation capabilities, promoting co-creation in conceptual art and brand design. Surveys show that about 67% of designers report AI tools save them over 30% of time on routine tasks [26]. Accordingly, design tool companies are integrating AI into their products; for example, Adobe's Firefly series [27] and Canva's Magic Design [28] offer not only text-to-image generation but also advanced functions like sketch optimization and style transfer.

Nevertheless, despite these technological gains, current AI-assisted design faces several shortcomings in practice, especially in traditional costume pattern design[9, 10, 11]. One key issue is the cultural context gap [29, 30]: when handling long-tail or region-specific cultural elements, models often produce results that only approximate intended meanings, demanding further manual adjustment and prompt iteration from designers. Additionally, current AI image generation systems, such as ComfyUI [31], support modular pipelines but lack flexibility and adaptive decision-making, relying heavily on manual setup. In reality, different models have distinct strengths, for example, GPT-Image-1 [7] excels in logical consistency, while Seedream 4.0 (known as “Doubao”) [32] is better at image segmentation but less so at creative pattern regeneration. Effective design workflows require dynamic adjustment and seamless integration of these tools, highlighting the need for agentic systems that can autonomously orchestrate and adapt tool usage to better support designers.

2.2 Traditional Costume Pattern Design

The design of traditional costume patterns typically follows a comprehensive process encompassing research and inspiration gathering, pattern element extraction and analysis, creative redesign, and digitalization with craft simulation. [33] Initially, designers study historical contexts and cultural semantics embedded in motifs through literature review, museum collections, and craft research to avoid superficial replication. [34] Subsequently, they deconstruct core motifs and analyze their formal characteristics(such as rhythmic lines, compositional rules, and color systems)while adapting them to contemporary needs through thoughtful reinterpretation. During the creative phase, designers reassemble motifs using techniques like rotation, mirroring, and collage, infusing them with modern narratives to extend traditional symbols into new contexts. [35] Finally, vectorization and color iteration are completed using digital tools like Illustrator, alongside simulating pattern placement on costume silhouettes and effects of embroidery or dyeing techniques to reduce trial-and-error costs in production. Though this workflow is relatively mature in practice, challenges remain, including fragmented knowledge, reliance on experience, and difficulties in quantifying craft constraints. [36] Moving forward, integrating knowledge-enhanced and agent-based systems that align cultural symbols, craft processes, and aesthetic norms is crucial.

3 FRAMEWORK OF AGENTIC SYSTEM

3.1 System Overview

We develop a multimodal, LLM-driven agentic system that operates in a closed loop of perception, retrieval, generation, reflection, and revision. As illustrated in Figure 1, when presented with user requirements and input images, the agentic system first evaluates and analyzes the content, determining whether online background knowledge searching is necessary. It then identifies the primary subject and adaptively employs background removal tools to segment and refine the target. Based on user needs and reference styles, the system dynamically retrieves relevant design experience and pattern and experiential knowledge from the curated knowledge base. Additionally, it can retrieve suitable reference style images from the style bank to guide the creation process. By integrating these resources into the generation pipeline, the system produces candidate patterns. Subsequently, the agent conducts self-assessment based on visual quality, iteratively revising the output to ensure normative compliance and achieve the desired creative expression.

In implementation, the large language model (instantiated with GPT-5 [37]) serves as the core "brain" of the agentic system, interfacing with a suite of tools including web search, knowledge base access, reference style image retrieval, background removal, and generative/editing modules. Specifically, SeedReam4.0 [32] is utilized for precise foreground extraction and background cleanup, while GPT-Image-1 [7] supports candidate generation and revision.

3.2 Curation and Retrieval of Knowledge Base

To enable professionally controllable and culturally coherent generation, we curate two text-only knowledge bases and one image-text style reference bank. Figure 2 illustrates the knowledge base curation pipeline.

Text Knowledge Bases. We collect 14 books (5 on design instructions and 9 on traditional art patterns) from which we use GPT-5 to extract and rewrite operational rules. This process yields 1,288 design experience entries and 582 pattern design norms. Two professional designers then independently review, harmonize terminology, and consolidate hierarchies to remove redundancy and resolve conflicts, resulting in 781 high-quality design experiences and 504 costume pattern norms. All entries are standardized and embedded using gpt-text-embedding-3. During inference, the user’s requirements and features extracted from the input image are also semantically embedded. The system then retrieves the top 10 most relevant design experiences and the top 10 pattern design norms based on cosine similarity for further conditioning.

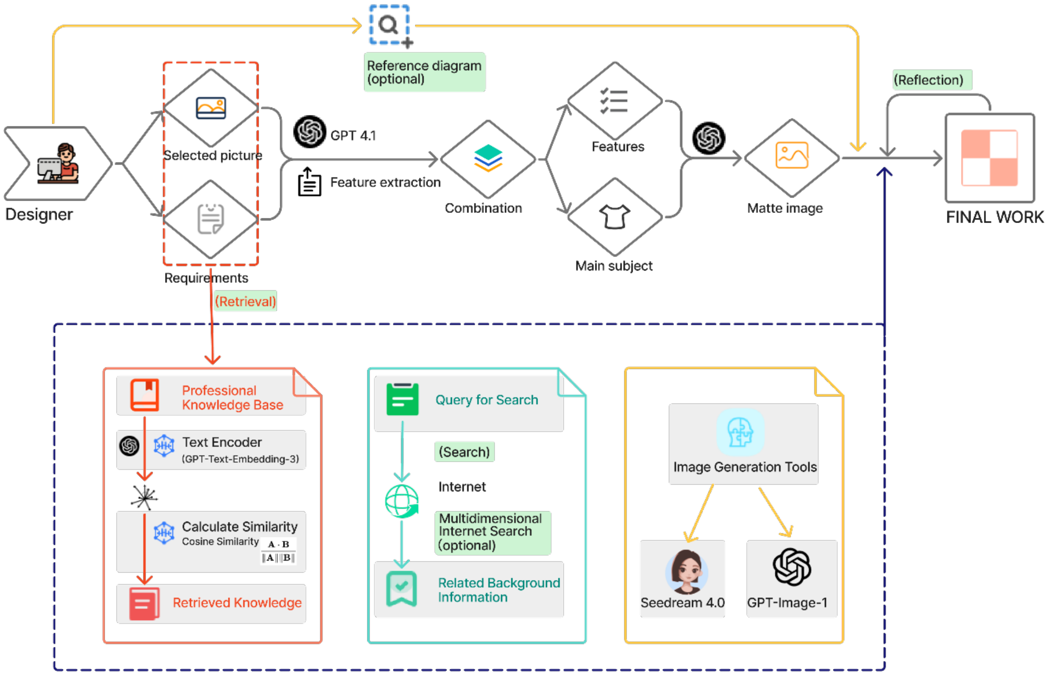


Figure 1. An overview of the agentic system.

Image-Text Style Reference Bank. We compile 20 representative style images commonly used in this domain, each captioned GPT-5 and subsequently verified by two independent designers. These captions provide structured style descriptors, such as color palette, composition schema, motif vocabulary, period cues, and indicative craft techniques. During inference, the agentic system automatically encodes user requirements and cross-retrieves the most suitable exemplar from the style bank as a style anchor.

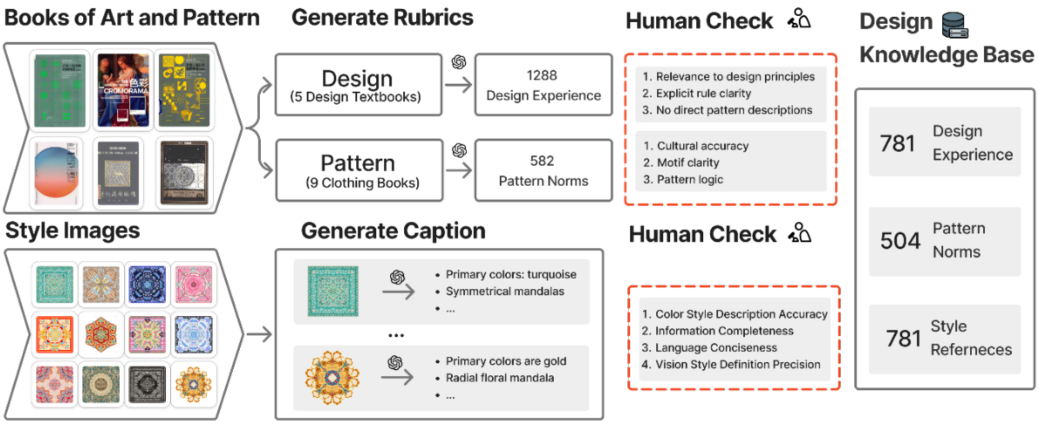


Figure 2. The construction pipeline of our knowledge base.

3.3 Agentic Workflow and Control Policy

Our system employs a layered, LLM-driven agent with dual visual-textual perception. A high-level controller orchestrates perception, retrieval, generation, reflection, and revision, and invokes tools such as web search, knowledge-base retrieval, and image-editing utilities. The agent maintains cross-turn memory, performs hierarchical prompt planning to prevent constraint dilution, and balances controllability with expressive freedom.

During operation process, the agent proceeds through the following states, with conditional branching and revisiting as needed:

- **Intent recognition and input analysis.** Upon receiving a user request, the agent identifies the category and focal subject, analyzes salient attributes and constraints, and infers the intended creative objective (ideation, variation, localization, etc.).
- **Dynamic web search.** The agent optionally queries the internet for cultural background,

historical lineage, and contemporary applications relevant to the costume and motif, summarizing verifiable insights as design context and inspiration.

- **Background removal.** After precise subject localization, the agent invokes a matting tool to extract the subject and clean the background, reducing off-target artifacts and noise. We use SeedReam4.0 for matting and, when necessary, localized inpainting for structural repair.
- **Text knowledge-base retrieval.** Conditioned on costume typology, user intent, and the web-derived context, the agent queries the curated textual knowledge bases to retrieve design-discipline rules and traditional pattern constraints. Retrieved items are merged into an actionable constraint set covering compositional hierarchy, layout logic, color systems, craft feasibility, etc.
- **Style reference retrieval.** If the user does not provide a style image, the agent searches the image relying on text style bank and selects the most suitable exemplar as a style anchor via cross-modal similarity and reranking. The reference is decomposed into operational variables for downstream conditioning for example palette, composition schema, motif lexicon, texture semantics and era cues.
- **Creative synthesis.** The agent assembles a hierarchical prompt plan: core constraints (cultural fidelity, technique or process feasibility, rule compliance) are anchored first, while secondary preferences (stylistic tendencies, palette refinements, layout adjustments, etc.) are layered in a controlled manner. It then adapts prompts and control signals to drive the image generator, using GPT-Image for candidate synthesis; masks and references are incorporated to align semantic intent, stylistic expression, and craft constraints within a shared conditioning space.
- **Self-reflection and iterative refinement.** The agent evaluates outputs along cultural feature retention, user requirement compliance, color matching degree, original pattern extraction degree, composition symmetry, and concrete element exclusion. If the composite score is below threshold, it diagnoses deficient dimensions, updates the constraint set and style variables, locally replans prompts, and triggers targeted edits using GPT-Image in editing mode (inpainting, instruction-based refinement, etc.). Iteration continues until convergence or budget limits are reached.

4 EVALUATION AND RESULTS

4.1 Benchmark Construction

To comprehensively and horizontally verify the comprehensive capabilities of various generative models in the task of traditional costume pattern generation, we first constructed a specialized test set, which has been jointly validated by 2 senior designers, based on the scientificity and representativeness of test data. This test set 10 classic image generation cases with typical cultural identifiers, and the case system emphasizes diversity: it not only covers differences in application scenarios, costume characteristics, and shooting angles, but also includes different categories of costumes. Meanwhile, it distinguishes between close-up shots of costume details and complete images with human figures, ensuring the diversity and representativeness of the cases.

In terms of baseline modes, we selected 4 representative mainstream image generation models that have demonstrated excellent performance in the field of general image generation, so as to ensure the authority and reference value of the comparative experiment. Among them, Qwen-Image [38], a multimodal generative model launched by Alibaba Group, has significant advantages in detail generation and scene restoration; GPT-Image-1 [7], relying on the large language model base of OpenAI, exhibits outstanding performance in text instruction understanding and cross-modal alignment capabilities; Seedream 4.0 [32] is a generative model developed by ByteDance focusing on the cultural and creative field, and it has long been well-known for "Doubao"; Gemini-2.5-flash-image-preview [8], leveraging Google's accumulated multimodal technologies, possesses strong competitiveness in complex scene generation and the rationality of color matching. By selecting the aforementioned models with different technical routes and research backgrounds as baselines, we can more comprehensively compare and analyze the differences in generation capabilities of various models in the vertical field of traditional costume patterns, thereby avoiding evaluation biases caused by a single type of model.

In the aspect of metrics, we constructed a scoring standard consisting of five dimensions to achieve a comprehensive evaluation:

- Cultural Relevance: It mainly examines whether the generated results can accurately match the target cultural background. It not only requires avoiding symbols or elements inconsistent with the cultural context, but also needs to reflect cultural uniqueness and regional differences on the whole.

- Pattern Accuracy: It focuses on the consistency between the generated patterns and the original input in terms of detail presentation and color restoration, and eliminates fabricated or distorted content.
- Aesthetics: From the perspective of design aesthetics, it judges the rationality of the generated results in terms of symmetry and balance, coordination between the whole and parts, diversity and unity, as well as the contrast and harmony of colors and textures.
- Perceived Usability: It is used to measure the simplicity of model operation, the clarity of input requirements and the fluency of generation speed.
- Scene Adaptability: It mainly tests the robustness of the model under scenarios such as different shooting angles, pattern defects, blurred input, and interference from characters or complex backgrounds.

In the implementation of quantitative evaluation, 2 professional designers conducted quantitative scoring on the generated results of each model using a 5-point Likert scale in accordance with the above evaluation criteria, so as to ensure the objectivity and professionalism of the evaluation results. The two experts first scored the results independently and then compared their ratings. If there was a discrepancy, they would discuss their reasoning to agree on a final, unified score.

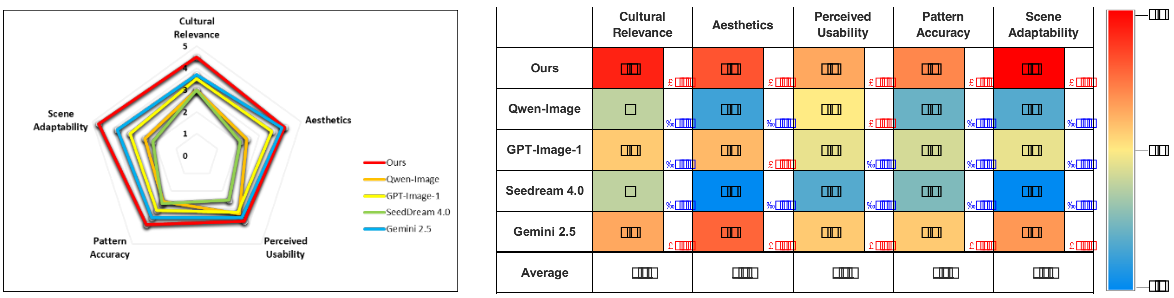
4.2 Quantitative Results

Figure 3 provides a comparative visualization of the quantitative evaluation across five key dimensions. As shown in the radar chart (Fig. 3a), our agentic system demonstrates clear and consistent advantages over all baselines. Specifically, our method achieves the highest scores in Cultural Relevance (4.5), Scene Adaptability (4.7), and Pattern Accuracy (3.9), indicating its strong capacity to generate culturally coherent, robust, and professionally accurate costume patterns. In Aesthetics (4.2), our model also outperforms most baselines, especially in color harmony and compositional balance, with only Gemini-2.5 showing similar performance (4.1).

The heatmap in Fig. 3b further highlights that our system's scores are above the average in all dimensions, reflecting a well-balanced and generalizable design capability.In contrast, models such as Qwen-Image and Seedream 4.0 perform less consistently, especially in Pattern Accuracy and Scene Adaptability. GPT-Image-1 and Gemini-2.5 achieve moderate results, with Gemini-2.5 being competitive in aesthetics but less reliable in cultural relevance and precision.

Furthermore, our system demonstrates a rare dual strength by scoring highly in both Cultural Relevance and Perceived Usability (3.7), a combination seldom achieved by baseline models. This indicates its ability to balance cultural authenticity with practical design experience, reducing the trade-off typically observed between these dimensions. In addition, the system's exceptional performance in Scene Adaptability (a full 0.9 points higher than the next best model) suggests its outputs are not only visually coherent but also robust across diverse design contexts and usage scenarios.

Overall, these results confirm that our knowledge-augmented agentic system significantly improves both the normative quality and adaptability of traditional costume pattern generation, delivering professional-level outputs and a more user-friendly workflow compared to existing mainstream models.



(a) Radar Chart *(b) HeatMap*

Figure 3. Comparison between our system against baselines.

4.3 Case Study

To complement our quantitative findings and provide an intuitive demonstration of the generation process, we conduct a detailed case study (as shown in Figure 4). The agentic system works by first extracting the core visual subject from the original costume image and then generating a new pattern based on this extracted subject.

The original images cover a wide range of traditional costume forms, from cloud shoulder pad with a clear outer outline (like Case 1) to full garments with complex structural details (such as Cases 5,6 and 8). Despite the differences in decoration styles, scales, and background complexity, our system can consistently isolate the core visual subject with high precision. For full garments (Cases 2,5,6,8), it effectively separates the garment from cluttered backgrounds (such as mannequins or exhibition settings) and retains key design features. For detailed shots of different costume accessories (Cases 3 and 4), the system is capable of learning their styles, standardizing image expansion, and accurately extracting the style of core patterns. For costume images with tricky shooting angles or incomplete forms (Cases 2 and 9), it can achieve excellent correction. As for costume photos with human figures present, our reflection function plays a key role: after effective reflection, it can well eliminate the human figures (Cases10), focus on the details of costume patterns, and conduct reconstruction design. Using these extracted subjects, our model generates patterns that balance cultural fidelity and creative design. In terms of cultural relevance, the generated patterns match the cultural context of the original costumes. For example, Case 5, inspired by an orange - hued traditional robe, produces a pattern with architectural motifs typical of the same cultural system, avoiding mismatched symbols. In terms of pattern accuracy and aesthetics, the generated patterns are visually consistent with the extracted subjects in color tone and motif style while introducing new and aesthetically pleasing designs. Take Case 2: its generated pattern inherits the blue palette and floral themes of the cut - out garment section but reinterprets them into a symmetric, decorative tile pattern with enhanced visual rhythm. In terms of scene adaptability, even when original images have flaws (like the partially obscured garment in Case 7), the generated pattern remains cohesive, showing the model's robustness to input imperfections.

Figure 4. Case study of generations inside our agentic system.

4.4 Limitations

A key limitation of this study is its exclusive reliance on human expert evaluation. We did not implement automated or fully objective indicators to assess the generated patterns, which makes the evaluation process less scalable and reproducible. While artistic quality is inherently subjective, future work could address this by integrating computational proxies for aesthetic appeal, such as symmetry indices or color harmony scores. Furthermore, a promising direction is to explore the "LLM-as-a-judge" paradigm, leveraging large multimodal models to provide automated, scalable feedback on the designs. This would complement expert opinions and contribute to a more robust evaluation framework.

5 CONCLUSIONS

In this work, we present a knowledge-augmented agentic system specifically designed for traditional costume pattern creation. By integrating a curated professional knowledge base and an adaptive, LLM-driven workflow, our system effectively addresses the limitations of conventional generative models in cultural fidelity, aesthetic quality, and design compliance. Comprehensive experiments demonstrate that our approach consistently outperforms leading baseline models across key dimensions, including cultural relevance, pattern accuracy, and scene adaptability. These results highlight the system's potential to streamline professional design processes and provide reliable, high-quality outputs for both practitioners and researchers. Future work will explore expanding the knowledge base and enhancing multimodal interaction to support broader application scenarios in cultural heritage design and beyond.

REFERENCES

[1] Watkins P. Garment pattern design and comfort. *Improving comfort in clothing.* Woodhead Publishing, 2011, pp.245–277.

[2] Gao X, Yezhova O. Chinese traditional patterns and totem culture in modern clothing design. *Art and Design*, 2023.

[3] Smithers T, Conkie A, Doheny J, et al. Design as intelligent behaviour: an AI in design research programme. *Artificial Intelligence in Engineering*, 1990, 5(2), pp.78–109.

[4] Liao Q V, Gruen D, Miller S. Questioning the AI: informing design practices for explainable AI user experiences. In: Proceedings of the 2020 CHI conference on human factors in computing systems, 2020, pp.1–15.

[5] Midjourney. Midjourney Introduction. Available: https://www.midjourney.com/home [Accessed on 2025, 27 September].

[6] Rombach R, Blattmann A, Lorenz D, et al. High-resolution image synthesis with latent diffusion models. In: Proceedings of the IEEE/CVF conference on computer vision and pattern recognition, 2022, pp.10684–10695.

[7] OpenAI. Introducing our latest image generation model in the API. Available: https://openai.com/index/image-generation-api/ [Accessed on 2025, 27 September], (2025, 23 April).

[8] Google. Introducing Gemini 2.5 Flash Image, our state-of-the-art image model. Available: https://developers.googleblog.com/en/introducing-gemini-2-5-flash-image/ [Accessed on 2025, 27 September], (2025, 26 August).

[9] Tang Y, Zhang N, Ciancia M, et al. Exploring the impact of AI-generated image tools on professional and non-professional users in the art and design fields. In: Companion Publication of the 2024 Conference on Computer-Supported Cooperative Work and Social Computing, 2024, pp.451–458.

[10] Xi C, Chung J. Research on the Use of AI for Digitalization and Dissemination of Traditional Chinese Art Patterns. *International Journal of Advanced Culture Technology*, 2024, pp.231–236.

[11] Liu M, Zhou B. Innovative design of Chinese traditional textile patterns based on conditional generative adversarial network. In: International Conference on Human-Computer Interaction. Cham: Springer International Publishing, 2022, pp.234–245.

[12] Lan Z, Zhang Y. Opportunities, Critiques, and Challenges of Chinese Fashion Design in the Era of Artificial Intelligence. In: Proceedings of the 4th International Conference on Culture, Design and Social Development (CDSD 2024). Springer Nature, 2025, 917, p.391.

[13] Gero J S. Ten problems for AI in design. In: Workshop on AI in Design, IJCAI-91, 1991.

[14] Feng Y, Wang X, Wong K K, et al. Promptmagician: Interactive prompt engineering for text-to-image creation. *IEEE Transactions on Visualization and Computer Graphics*, 2023, 30(1), pp.295–305.

[15] Gu J, Han Z, Chen S, et al. A systematic survey of prompt engineering on vision-language foundation models. arXiv preprint arXiv:2307.12980, 2023.

[16] Chen W, Hu H, Saharia C, et al. Re-imagen: Retrieval-augmented text-to-image generator. arXiv preprint arXiv:2209.14491, 2022.

[17] Sheynin S, Ashual O, Polyak A, et al. Knn-diffusion: Image generation via large-scale retrieval. arXiv preprint arXiv:2204.02849, 2022.

[18] Hu E J, Shen Y, Wallis P, et al. Lora: Low-rank adaptation of large language models. ICLR, 2022, 1(2), p.3.

[19] Ruiz N, Li Y, Jampani V, et al. Dreambooth: Fine tuning text-to-image diffusion models for subject-driven generation. In: Proceedings of the IEEE/CVF conference on computer vision and pattern recognition, 2023, pp.22500–22510.

[20] Gal R, Alaluf Y, Atzmon Y, et al. An image is worth one word: Personalizing text-to-image generation using textual inversion. arXiv preprint arXiv:2208.01618, 2022.
[21] Verganti R, Vendraminelli L, Iansiti M. Innovation and design in the age of artificial intelligence. *Journal of Product Innovation Management*, 2020, 37(3), pp.212–227.
[22] Stige Å, Zamani E D, Mikalef P, et al. Artificial intelligence (AI) for user experience (UX) design: a systematic literature review and future research agenda. *Information Technology & People*, 2024, 37(6), pp.2324–2352.
[23] Goodfellow I, Pouget-Abadie J, Mirza M, et al. Generative adversarial networks. *Communications of the ACM*, 2020, 63(11), pp.139–144.
[24] Croitoru F A, Hondru V, Ionescu R T, et al. Diffusion models in vision: A survey. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 2023, 45(9), pp.10850–10869.
[25] OpenAI. DALL·E 2 can create original, realistic images and art from a text description. Available: https://openai.com/index/dall-e-2/ [Accessed on 2025, 27 September], (2022, 25 March).
[26] Shen Y, Yu F. The influence of artificial intelligence on art design in the digital age. *Scientific Programming*, 2021, 2021(1), p.4838957.
[27] Angelova N. The capabilities of the art-oriented artificial intelligence Adobe Firefly and its visual advantages and disadvantages. *Journal "Fundamental Sciences and Applications"*, 2024, 30(1), pp.1–10.
[28] Rahma D N, Ramadhani K A, Corazon M, et al. The influence of Canva application features on the graphic design confidence: a case study of college students. *Journal of Applied Multimedia and Networking*, 2024, 8(1), pp.60–67.
[29] Liu B, Wang L, Lyu C, et al. On the cultural gap in text-to-image generation. arXiv preprint arXiv:2307.02971, 2023.
[30] Kannen N, Ahmad A, Andreetto M, et al. Beyond aesthetics: Cultural competence in text-to-image models. arXiv preprint arXiv:2407.06863, 2024.
[31] Xu Z, Yang X, Wang Y, et al. ComfyUI-Copilot: An Intelligent Assistant for Automated Workflow Development. arXiv preprint arXiv:2506.05010, 2025.
[32] Team Seedream, et al. Seedream 4.0: Toward Next-generation Multimodal Image Generation. Available: https://arxiv.org/abs/2509.20427 [Accessed on 2025, 27 September], (2025, 24 September).
[33] He G. and Gao S. Digital Translation of Traditional Textiles: Interactive Design Applications Based on Chinese Fabric Motifs. *Textile & Leather Review*, 2025, 8, 627–650.
[34] Shin M.J., Cassidy T. and Moore E.M. Design Reinvention for Culturally Influenced Textile Products: Focused on Traditional Korean Bojagi Textiles. *Fashion Practice*, 2015, 7(2), 175–198.
[35] An M.H. and Jang A.R. Development of textile pattern design by M. C. Escher's tessellation technique using chaekgeori icons. *Fashion and Textiles*, 2023, 10, Article No. 15.
[36] Hu T., Xie Q., Yuan Q., Lv J. and Xiong Q. Design of ethnic patterns based on shape grammar and artificial neural network. *Alexandria Engineering Journal*, 2020, 60, doi:10.1016/j.aej.2020.11.013.
[37] OpenAI. GPT-5 is here. Available: https://openai.com/gpt-5/ [Accessed on 2025, 27 September], (2025, 07 August).
[38] Wu C, Li J, Zhou J, et al. Qwen-image technical report. arXiv preprint arXiv:2508.02324, 2025.