Textile & Leather Review

ISSN 2623-6281| www.tlr-journal.com | 10.31881/TLR

A Human-Centered AIGC Framework for Inclusive Fashion Design: Mitigating Bias for East Asian (Chinese) Elderly

Hongcai Chen, Yongshun Che, Vongphantuset Jirawat, Sirivesmas Veerawat, Yan Wang

How to cite: Chen H, Che Y, Jirawat V, Veerawat S, Wang Y. A Human-Centered AIGC Framework for Inclusive Fashion Design: Mitigating Bias for East Asian (Chinese) Elderly. Textile & Leather Review. 2025; 8:1013-1043. https://doi.org/10.31881/TLR.2025.1013

How to link: https://doi.org/10.31881/TLR.2025.1013

Published: 16 December 2025

A Human-Centered AIGC Framework for Inclusive Fashion Design: Mitigating Bias for East Asian (Chinese) Elderly

Hongcai CHEN[1,2], Yongshun CHE[3], Vongphantuset JIRAWAT[2], Sirivesmas VEERAWAT[2], Yan WANG[1*]

[1]Fujian Digital Media Economy Research Center, Minjiang University, Fuzhou 350108, Fujian, China

[2]Faculty of Decorative Arts, Silpakorn University, Bangkok 10200, Thailand

[3]Quanzhou Digital Cloud Valley Information Industry Development Co., Ltd., Quanzhou, 352102, Fujian, China

*2060@mju.edu.cn

Article

https://doi.org/10.31881/TLR.2025.1013

Received 23 October 2025; Accepted 7 November 2025; Published 16 December 2025

ABSTRACT

This paper applies human-centered Artificial Intelligence-Generated Content (AIGC) techniques to fashion design for the East Asian elderly population, with a specific focus on the Chinese cultural context, situated within the Industry 5.0 framework. While AIGC offers substantial opportunities for design automation and personalization, mainstream applications frequently exhibit algorithmic bias and lack cultural inclusivity. To address these challenges, we propose and evaluate a human-centered AIGC framework that integrates deep personalization—user-specific model training using Low-Rank Adaptation (LoRA)—with designer-centric evaluation via structured assessment using the Fuzzy Analytic Hierarchy Process (FAHP). Employing a mixed-methods approach, which combines two design experiments and FAHP analysis involving 22 designers and experts, we investigate how AIGC can enhance fashion design for this marginalized demographic. The first experiment examines AIGC's potential for digital prototyping to reduce material waste, directly supporting Industry 5.0's sustainability pillar. The second experiment utilizes LoRA technology to create a deeply personalized collection for a representative Chinese user, demonstrating a viable pathway to mitigate representational algorithmic bias and improve cultural inclusivity. FAHP analysis reveals that designers prioritize AIGC for enhancing design efficiency, iteration speed, innovation, and diversity. The findings culminate in an integrated framework that leverages AIGC for sustainable and socially responsible design, providing practical insights for the development of human-centered AI applications that empower both designers and users.

KEYWORDS

human-centered AI, East Asian elderly fashion, digital prototyping, algorithmic bias mitigation, sustainable textile

INTRODUCTION

As the global fashion industry transitions into the Industry 5.0 era, Artificial Intelligence-Generated Content (AIGC) is fundamentally transforming design practices. Industry 5.0 emphasizes three core pillars: human-centricity, sustainability, and resilience. In contrast to Industry 4.0's focus on automation, Industry 5.0 advances a balanced concept of human-machine collaboration, leveraging artificial intelligence for efficiency while preserving the intuition and creativity of human designers. In this context, AIGC functions not merely as an automation tool but as a catalyst for enhanced creativity, enabling personalized solutions and facilitating iterative learning.

Our framework operationalizes the three pillars of Industry 5.0. We address human-centricity by placing users' personal characteristics, cultural backgrounds, and aesthetic preferences at the core of the design process through deep personalization. Sustainability is achieved via digital prototyping, which significantly reduces physical sampling and material waste. Resilience is enhanced by developing methodologies that enable the fashion industry to serve previously marginalized demographics, specifically East Asian (Chinese) elderly populations, often overlooked in both mainstream fashion and emerging technology applications.

AIGC's transformative potential is evident in its broad applications and its reshaping of collaborative design models. In fashion, researchers have achieved automatic clothing matching using techniques such as Attribute-GAN [1] and have validated the feasibility of using tools like Midjourney for fashion design development [2]. Projects such as DeepWear have demonstrated practical applications of collaborative design between humans and AI [3], and this impact extends beyond the fashion industry [4]. Scholars have conducted comprehensive reviews of AI applications in fashion [5] and have developed large-scale datasets like FIRST to support text-driven design innovation [6]. Cross-disciplinary applications—from envisioning personalized fashion [7] to studying AI's role in collaborative qualitative analysis [8]—collectively demonstrate that AI augments rather than replaces human creativity.

Within the specific workflow of fashion design, AIGC drives industry development on multiple levels. It addresses industry challenges by supporting sustainable practices [9] and empowers AI-driven fashion social networking services combined with e-commerce [10]. On a technical level, reference-based design using diffusion models enables structure-aware style transfer, as demonstrated by recent algorithmic advancements [11]. Research into sustainability highlights the prospects of smart clothing [12], while other studies examine methodologies for ensuring AI fairness in data analytics [13]. These technological advancements fundamentally alter design workflows, as explored in research examining how generative algorithms reshape the creative process [14]. Applications range from image recognition technology [15] to AI-driven fashion trend forecasting [16]. Comprehensive reviews have outlined new opportunities for AI-driven design aesthetics and manufacturing processes [17,18], and recent studies discuss how AI disrupts traditional processes in design education [19]. Yin et al. [20] demonstrate the integration of tools like Midjourney into design systems for future-oriented innovation, and Choi et al. [21] have developed automated design systems reflecting fashion designers' work processes.

Despite AIGC's immense potential, significant challenges accompany its application. A prominent issue is aesthetic convergence, where AI-generated works exhibit monotony and repetition in style (Figure 1), as discussed by Kalpokas [22] regarding art in the age of AI reproduction, which limits true design innovation.

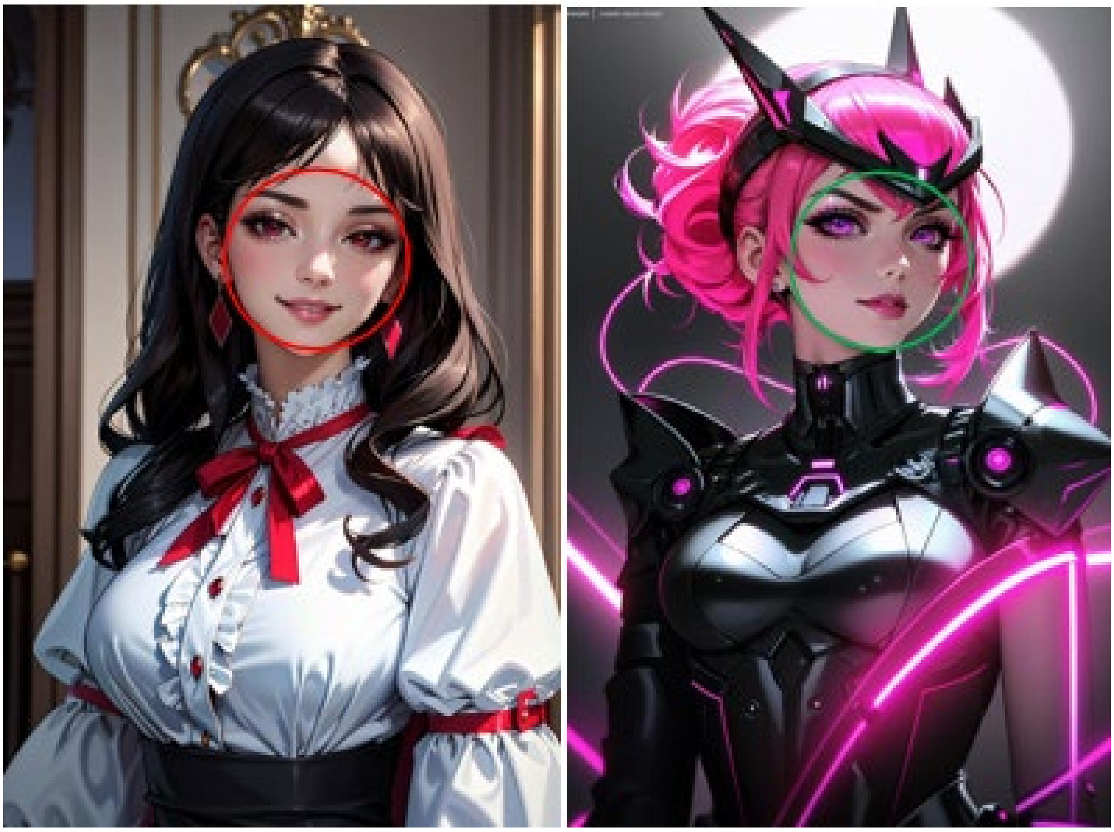

Figure 1. Convergence of imagery and aesthetics in AI-generated characters

A more serious concern is algorithmic bias. Due to the lack of diversity in training data, AIGC systems often produce content with biases and stereotypes, reflecting a mainstream—typically Western—aesthetic standard (Figure 2), thereby neglecting the diversity and identity of peripheral cultural groups. Gui Bonsiepe's center-periphery theory highlights longstanding cultural and economic imbalances in the design field [23,24]. Consequently, specific groups, such as East Asian elderly populations, are frequently overlooked in both mainstream fashion and emerging technology applications. Furthermore, a significant gap exists between the rapid development of AIGC technology and its integration into design education. Adeshola et al. [25] emphasize the disconnect between AI tools and design curricula. McCardle [26] discussed challenges in integrating smart technology as early as 2002, while Luckin and Cukurova [27] identified a general lack of AI literacy among educators and students. Luo and Wang [28] analyzed the crises facing design education in the AIGC era, and Gu et al. [29] raised ethical concerns about overreliance on AI potentially weakening students' critical thinking, even as scholars like Zhang [30] propose curriculum integration strategies.

Figure 2. Exhibition of AI-generated image discrimination and stereotypes (Three Shadows, Xiamen, captured by the research team)

This research addresses a central question: Despite AIGC's vast potential for efficiency and personalization, how can we leverage this technology to address aesthetic convergence and algorithmic bias, thereby providing genuinely inclusive, culturally sensitive, and functional design solutions for groups marginalized by the mainstream fashion industry? We focus specifically on East Asian (Chinese) elderly populations. We acknowledge that Asia encompasses numerous distinct cultures, body types, and fashion sensibilities. Our study addresses the East Asian cultural context, with particular emphasis on Chinese elderly populations, from which our design representative and expert participants were drawn. The concept of cultural inclusivity derived here is limited to this specific context and cannot be generalized to all Asian elderly populations without further validation.

Research applying AIGC to meet the specific needs of this group is currently insufficient, presenting a clear market and academic gap. To address this challenge, we propose and evaluate a human-centered AIGC fashion design framework. This framework combines technological innovation with social responsibility. Through two design experiments and Fuzzy Analytic Hierarchy Process (FAHP) validation, we explore how AIGC—particularly through deep personalization achieved with technologies like Low-Rank Adaptation (LoRA)—can empower designers to create fashion products that are both sustainable and tailored to the specific needs of East Asian (Chinese) elderly populations. This study provides a viable theoretical framework and practical guidance for the inclusive application of AIGC in the fashion domain.

RESEARCH QUESTIONS, OBJECTIVES, AND SCOPE

Research Questions

Based on the opportunities and challenges of AIGC technology in fashion as outlined above, this study investigates a core issue. While current AIGC technology offers significant potential for improving efficiency and personalization, inherent algorithmic biases and aesthetic convergence often result in the marginalization of specific social groups, such as East Asian (Chinese) elderly populations. Therefore, the central research question (RQ) of this study is:

RQ: How can we construct and evaluate a human-centered AIGC fashion design framework to effectively meet the personalized, cultural, and functional needs of East Asian (Chinese) elderly populations, while addressing the biases and limitations of existing AIGC technologies?

To systematically address this issue, we break it down into three interconnected sub-questions (SQs), examining the core question from technological, designer, and industry perspectives:

- **SQ1: How can we apply personalization technologies such as LoRA to mitigate representational algorithmic biases (e.g., Western aesthetic dominance and underrepresentation of East Asian elderly features) in mainstream AIGC models, thereby generating fashion designs with cultural resonance and personal style for East Asian elderly users?**
- **SQ2: Within this human-centered framework, what are the key factors that fashion designers prioritize when using AIGC for creation? How does AIGC influence their creative ideation and decision-making processes?**
- **SQ3: How does the proposed AIGC framework contribute to sustainable and inclusive design practices under the Industry 5.0 paradigm by supporting digital prototyping and iteration?**

Research Objectives

To address the research goals and systematically answer the research questions, this study sets out four specific objectives. The primary objective is to develop and test a personalized AIGC design workflow, applying LoRA technology by fine-tuning a model based on the personal data of a representative user. The aim is to generate fashion concepts with high cultural and stylistic specificity, directly addressing the first sub-question regarding technological application (SQ1).

The second objective is to identify and quantify the key factors designers consider when using AIGC. We employ the FAHP to systematically collect and analyze the elements and their relative importance that designers focus on when designing for a demographic such as East Asian (Chinese) elderly individuals, providing an in-depth answer to the designer's perspective (SQ2).

The third objective evaluates the framework's potential in promoting sustainable design. By analyzing its role in supporting rapid digital prototyping and reducing the need for preliminary physical sampling, we explore its practical value in minimizing material waste and enhancing design efficiency, providing empirical evidence for the sustainability aspect (SQ3).

Ultimately, these steps converge into the fourth and final objective: to propose an integrated, human-centered AIGC design framework. The study synthesizes practical experience from the design experiments and quantitative analysis from FAHP to distill a framework that is both theoretically robust and practically instructive. This provides a clear pathway for the fashion industry to leverage AIGC for more inclusive and socially responsible design, thus comprehensively addressing the central RQ.

Research Scope

To ensure the depth and feasibility of the research, we clearly define the scope as follows. The target population is the East Asian (Chinese) elderly community, treated as a representative user group marginalized by the mainstream fashion industry for an in-depth case analysis. We acknowledge that Asia is a vast and culturally diverse continent encompassing numerous distinct cultures, languages, body types, aesthetics, and fashion traditions. Our study's focus on East Asian, specifically Chinese, elderly populations reflects the cultural and geographic context of our user representative and expert participants. The findings regarding cultural inclusivity are specifically applicable to this East Asian (Chinese) context and cannot be generalized to all Asian elderly populations without further validation across different Asian cultural contexts. Future research should extend this framework to other Asian regions (e.g., South Asian, Southeast Asian, Central Asian elderly populations) to validate broader applicability.

Technologically, this study primarily investigates image generation AI tools, represented by Stable Diffusion and Midjourney, with LoRA as the core technology for deep personalization. Other AI algorithms are not considered in depth. Disciplinarily, this research is situated at the intersection of fashion design, human-computer interaction, and artificial intelligence application research, aiming to foster interdisciplinary dialogue and integration. The evaluation focus is on the effectiveness of the design process and the professional perspective of designers (analyzed via FAHP), rather than conducting a large-scale market feasibility or consumer acceptance survey, thereby ensuring the research remains focused on design methodology innovation.

METHODOLOGY AND DESIGN

Overall Research Design

To systematically answer the research questions, we adopted a mixed-methods approach, integrating qualitative design experiments with quantitative survey analysis to explore the topic from both practical and theoretical perspectives. The overall research framework consists of two progressive design experiments followed by FAHP evaluation. The design experiments serve as the core exploratory tool for understanding AIGC's potential and limitations in specific design contexts through hands-on practice. The first experiment focuses on digital prototyping feasibility for sustainability, while the second concentrates on deep personalization for bias mitigation. Subsequently, FAHP analysis quantifies and validates key consideration factors for designers observed during the experiments. This research trajectory, moving from "how to do it" (the experimental process) to "why it is done this way" (designer decision-making), enables comprehensive addressing of the central research questions.

Operational Definitions of Key Framework Components

For clarity and precision, we provide operational definitions for the core technical components of our framework:

- **Deep Personalization:** Defined as the process of training user-specific LoRA (Low-Rank Adaptation) models on personal datasets containing at least 20 high-resolution images of the target user captured across various angles, expressions, and scenarios. This enables the generation of fashion concepts authentically reflecting (1) the user's physical features (facial characteristics, body proportions, skin tone), (2) cultural background (traditional aesthetic preferences, symbolic meanings), and (3) individual aesthetic preferences (style directions, color preferences, formality levels). Deep personalization fundamentally alters the model's learned representations to center on a specific individual, going beyond surface-level customization.
- **Designer-Centric Evaluation:** Defined as a structured analytical approach to understanding designers' decision-making processes and priorities when using AIGC tools in their creative workflow. Operationalized through FAHP analysis, this method systematically captures and quantifies designers' relative preferences across 16 specific factors, organized into four major dimensions: (1) accurate understanding of user needs, (2) design innovation and diversity, (3) design efficiency and iteration speed, and (4) cultural adaptability and inclusiveness. This evaluation privileges professional designers' expert judgment, recognizing that successful human-AI collaboration requires understanding how AI tools integrate into professional creative practices.
- **Algorithmic Bias Mitigation:** Grounded in established human-computer interaction frameworks [31], we specifically address representational algorithmic bias, defined as the systematic underrepresentation or misrepresentation of East Asian elderly individuals in AI-generated fashion imagery. This bias manifests in three forms: (1) Western aesthetic dominance—AI models trained predominantly on Western fashion datasets generate elderly figures reflecting Western facial features, body proportions, and aging characteristics; (2) Youth-centric representation—mainstream AIGC models overwhelmingly depict younger demographics, with elderly individuals often

stereotyped; and (3) Cultural insensitivity—AI-generated clothing designs for elderly users reflect Western traditions, neglecting culturally specific preferences, symbolic meanings, and functional requirements relevant to East Asian elderly populations.

Bias mitigation is evaluated through qualitative comparative analysis. Two sets of fashion design concepts were generated: (1) mainstream AIGC outputs using standard Stable Diffusion models with text prompts describing East Asian elderly fashion, and (2) LoRA-personalized outputs using a user-specific trained model. Two independent fashion design experts conducted blind comparative evaluations across five dimensions: facial feature authenticity, cultural appropriateness, age-appropriate representation, stylistic diversity, and functional suitability. We acknowledge the limitations of qualitative evaluation and the absence of standardized benchmarks for fashion-specific AIGC applications. Future research should develop quantitative bias metrics.

We clarify that our claim is specifically about mitigating representational bias, not eliminating all forms of algorithmic bias. LoRA-based personalization mitigates representational underrepresentation by centering the AI model's outputs on a specific individual's actual characteristics. We do not claim to address other forms of algorithmic bias (e.g., allocation bias in recommendation systems). Our contribution lies in demonstrating a technically feasible pathway for reducing Western aesthetic dominance and youth-centricity in mainstream AIGC fashion applications.

Design Experiment 1: Digital Prototyping for Sustainable Design

The first experiment evaluated AIGC's potential to support sustainable design practices through digital prototyping, directly addressing Industry 5.0's sustainability pillar (SQ3). Rather than validating general AIGC feasibility (already established in literature [2,3,20]), we focused on demonstrating how digital prototyping can reduce physical sampling and material waste in the design iteration process for East Asian elderly fashion. We followed a streamlined Design Thinking process. In the Empathize stage, market research was conducted and a representative denim jacket popular among East Asian elderly consumers was selected (Figure 3). In the Define stage, the garment was analyzed using GPT-4 Vision to extract key design elements and generate style prompts. In the Ideate stage, Midjourney was used to generate approximately 100 digital concept images, enabling extensive design exploration without physical materials (Figure 4). These digital prototypes allowed designers to rapidly evaluate concepts in the Prototype stage. In the Test stage, five promising concepts were selected and one was physically realized through hand-painting modifications to the original garment (Figure 5).

Figure 3. Popular denim tops found in local markets (photo by the research team)

Figure 4. Stylish Asian elderly individuals styled in denim tops (generated by Midjourney V5.1)

Figure 5. The research team generated a rendering based on AI, collected feedback, and then created a secondary design for the denim top

Experiment 1 validated AIGC's utility for sustainable digital prototyping but revealed two key limitations: (1) the design process was simplified and did not fully incorporate complex garment manufacturing details; and (2) the lack of direct user involvement meant outputs might deviate from the target group's actual needs. These insights informed the deep personalization approach of Experiment 2.

Design Experiment 2: Deep Personalization Design and Implementation with LoRA Technology

To address the limitations identified in Experiment 1 and respond directly to SQ1, Experiment 2 focused on deep personalization design. The objective was to explore how LoRA technology can effectively mitigate the algorithmic biases of mainstream models. A representative real user—Ms. Chen, a senior fashion design lecturer over the age of 45—was invited to participate. Ms. Chen possesses a profound understanding of fashion and an independent aesthetic pursuit. Her explicit desire to explore her unique style in older age provided a valuable starting point for this experiment.

The core process extended beyond training and applying a personalized LoRA model to encompass a complete, AIGC-integrated custom garment design and production workflow, divided into the following stages:

Stage 1: Personalized Model Training and Initial Concept Generation: A dedicated training dataset was constructed by collecting 25 high-definition personal photos of Ms. Chen from various angles and scenarios (Figure 6). Each image was annotated with detailed keywords to train a LoRA model exclusive to Ms. Chen (Figure 7), ensuring that generated virtual likenesses were highly consistent with her facial features and expressions.

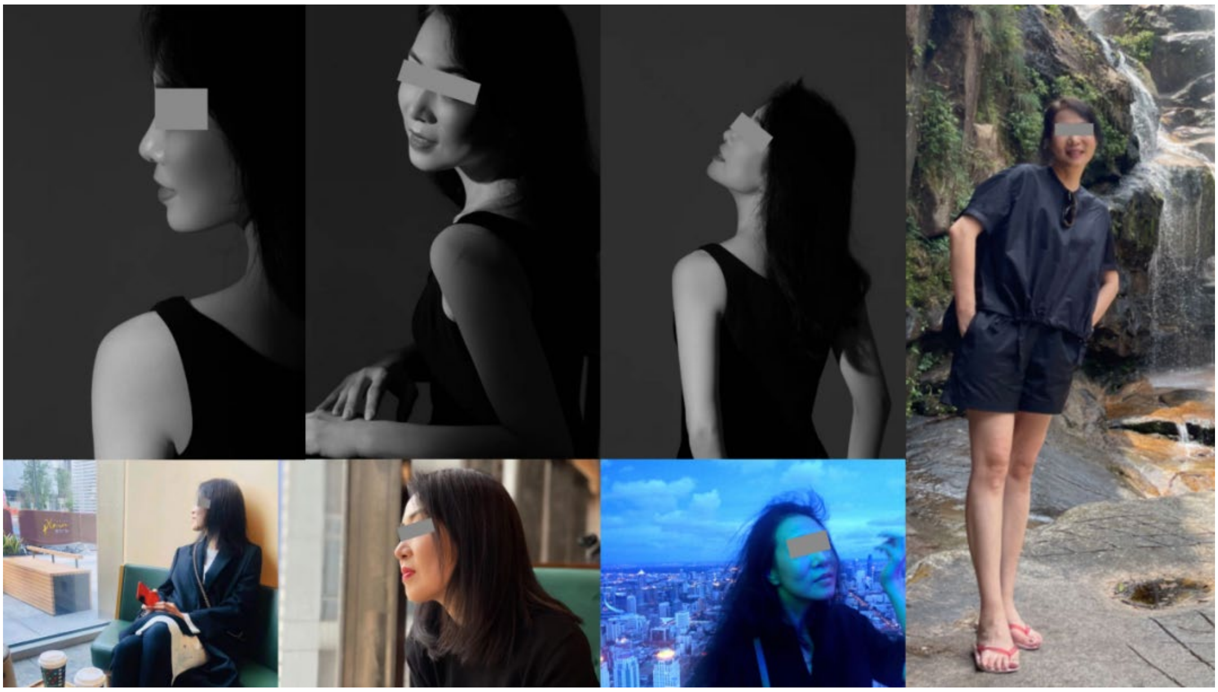

Figure 6. A collection of daily photo galleries used to train the LoRA model

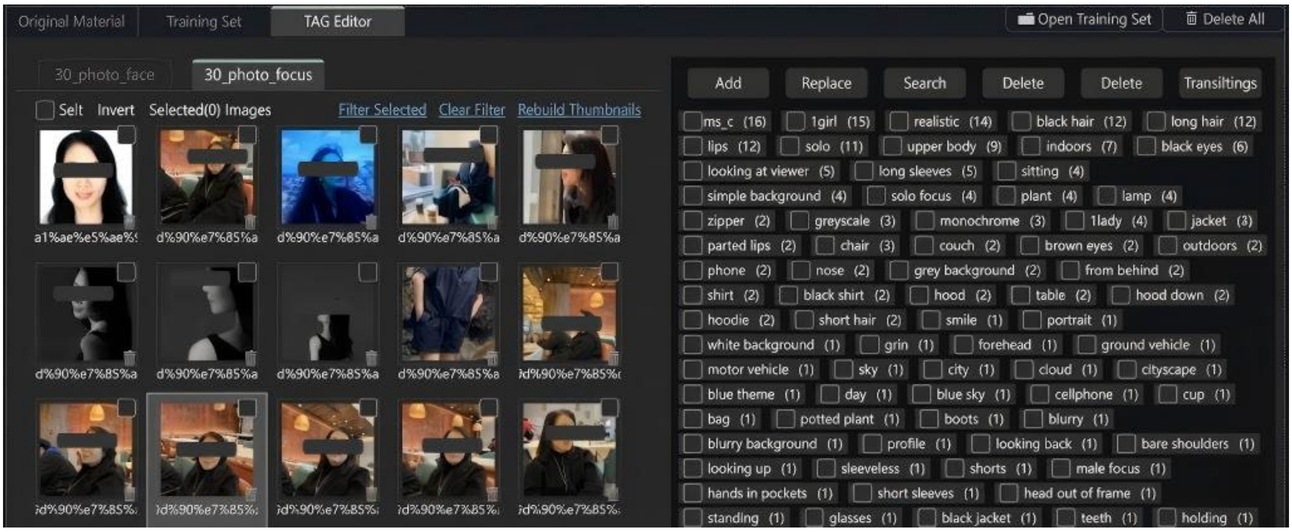

Figure 7. The process of generating LoRA: typing tagged words for each clip image

Following in-depth interviews with Ms. Chen, her desired stylistic directions (e.g., “cyberpunk combined with Chinese elements,” “new Chinese style”) were identified. The research team translated these style needs into precise prompts. By combining the trained LoRA model with Stable Diffusion, over 50 complete fashion design concept images were initially generated, forming a comprehensive concept series (Figures 8 and 9).

Figure 8. A series of fashion styles for Ms. Chen's elderly fashion

Figure 9. Finalized clothing styles and looks

Stage 2: Concept Deepening and Visual Reference (Look Book) Creation: Building on initial concepts, the research team utilized AIGC to enter a concept deepening phase for more precise communication with the user. Midjourney's */imagine* function was used to generate multiple visual effect collections (Look Books), providing Ms. Chen with rich visual references. The *-cref* (character reference) and *Vary (Region)* functions enabled fine-tuning of clothing details. Photoshop was used for post-processing, quickly generating various looks for user selection (Figures 10 and 11).

Figure 10. LOOK BOOK Sample 1

Figure 11. LOOK BOOK Sample 2

Stage 3: Design Discussion and Direction Refinement: Based on the AI-generated Look Book, online discussions were held with Ms. Chen. Feedback on visual references gradually refined the design direction, culminating in a preference for a green suit (Figure 12).

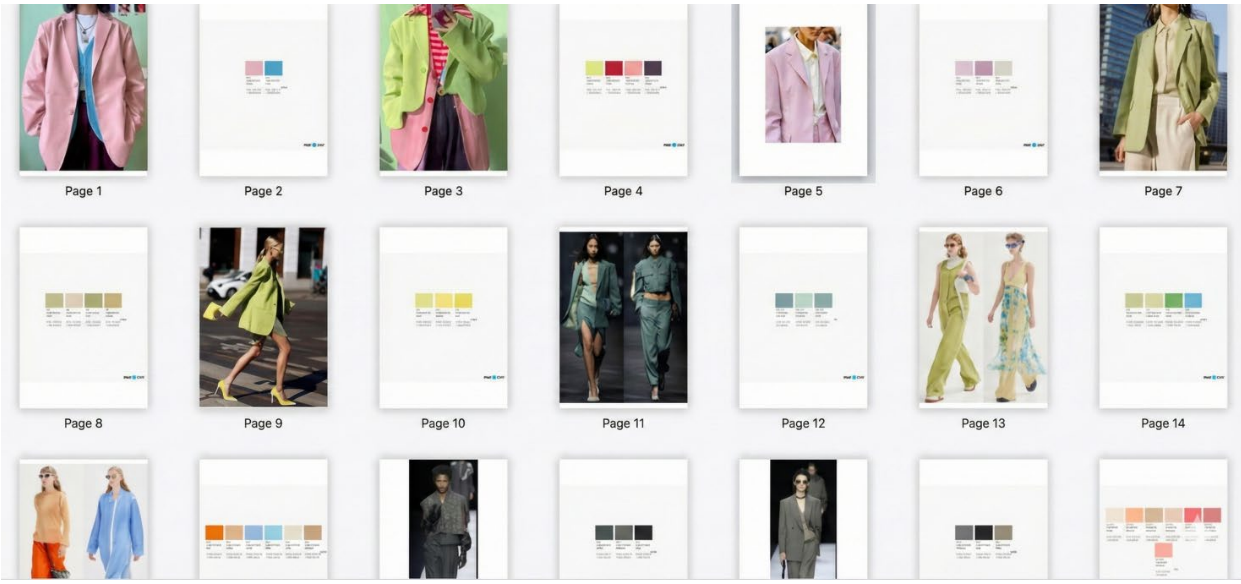

Figure 12. Style sketches organized from the discussion

Stage 4: Detailed Design Development and Digital Rendering: Stable Diffusion's ControlNet function was creatively applied to transform hand-drawn line art into realistic color renderings (Figure 13). Multiple color schemes and fabric texture renderings were generated, offering ample choice and new inspiration for the designers (Figures 14 and 15).

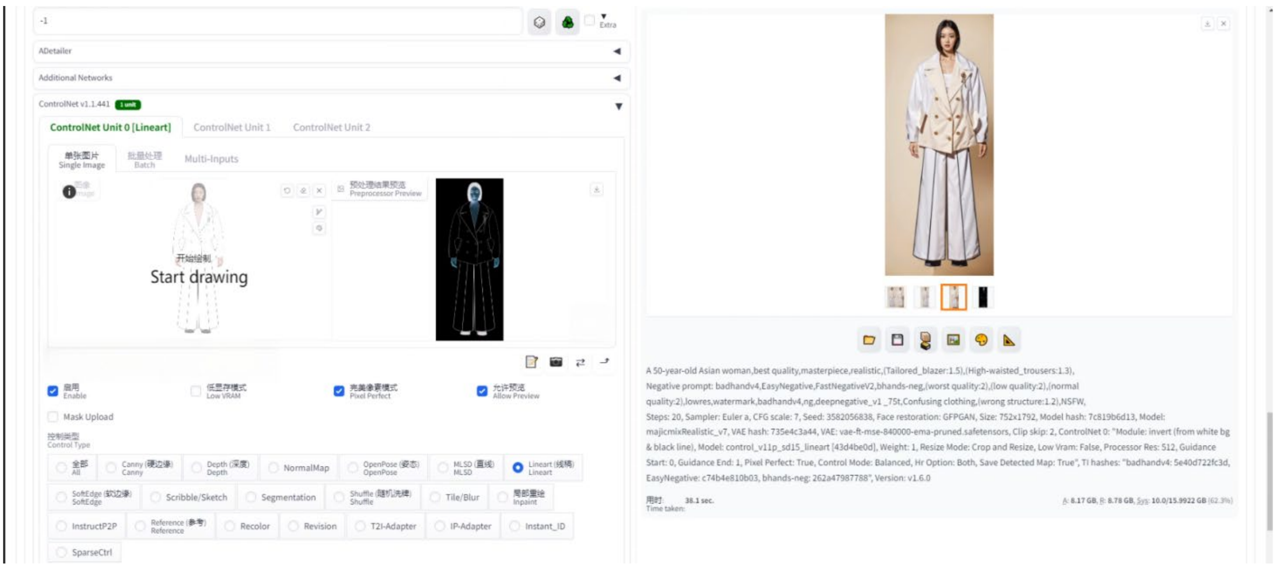

Figure 13. Line art coloring achieved through the ControlNet function of Stable Diffusion

Figure 14. Simulated garment effects 1

Figure 15. Simulated garment effects 2

Stage 5: Second Confirmation, Measurement, and Toile Production: After final design selection, an in-person meeting with Ms. Chen confirmed the design (Figure 16). Precise body measurements were taken (Figure 17), used to create paper patterns and a muslin prototype (toile), enabling intuitive feedback and adjustments.

Figure 16. The second-round requirement confirmation with Ms. Chen

Figure 17. The measurement process for Ms. Chen

Stage 6: Fitting, Effect Evaluation, and AI-Assisted Iteration: During the toile fitting session (Figure 18), feedback was collected from Ms. Chen, and AIGC technology assisted iteration. Photos of the toile fitting were imported into Stable Diffusion, using *img2img* and ControlNet's Tile functions (Figure 19) to recolor the photos while preserving garment structure, visually demonstrating different colors and fabrics (Figure 20). Ms. Chen proposed specific modifications, which were incorporated into the design and paper patterns (Figure 21).

Figure 18. Photo of the toile being worn

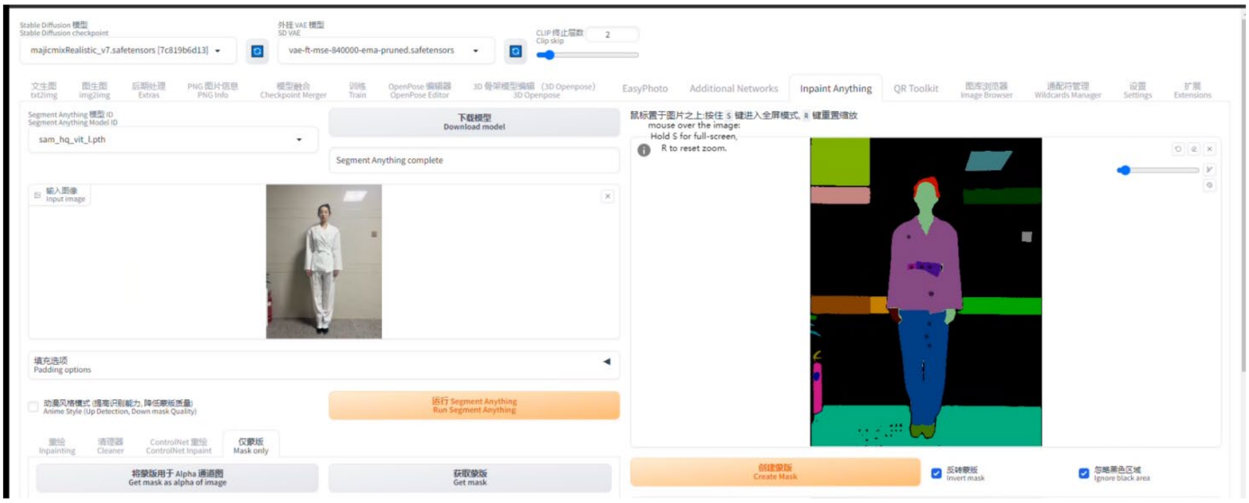

Figure 19. Processing the toile photo using Stable Diffusion

Figure 20. Simplified coloring effect images generated by Stable Diffusion

Figure 21. Modified style drawings based on user feedback

Stage 7: Final Garment Production and Studio Photoshoot: The optimized patterns were used to produce the final garment, and Ms. Chen participated in a professional studio photoshoot (Figure 22), providing final feedback on garment details.

Figure 22. Studio photos of the final ready-to-wear garment

This experiment deeply integrated AIGC technology with traditional bespoke tailoring, successfully creating a highly personalized garment for the target user. More importantly, it validated a comprehensive human-computer collaborative design framework, from abstract requirements to physical garment. The framework effectively utilizes AI to overcome biases such as the "Western Gaze," centering the user's personal characteristics, cultural background, and aesthetic preferences within the design process.

Quantitative Analysis: Fuzzy Analytic Hierarchy Process (FAHP)

Following the two design experiments, we conducted a quantitative study to address SQ2: identifying and quantifying the key factors designers prioritize when using AIGC for creation.

Justification for FAHP Methodology: While the finding that designers value efficiency and innovation may seem self-evident, FAHP provides critical insights beyond these expected results: (1) Quantified relative importance—FAHP reveals precisely how much more designers prioritize efficiency (global weight 0.3923) compared to other factors; (2) Unexpected hierarchies—FAHP revealed counterintuitive findings, such as "Accurate Understanding of User Needs" receiving relatively low priority (0.1486), suggesting designers currently view AIGC primarily as a tool for empowering their own creativity; (3) Structural insights—The high weight for "Inclusive Design Practices" (relative weight 0.3781) within the Cultural Adaptability dimension validates that our framework's focus on marginalized demographics resonates with designers' ethical priorities.

Sample Size Considerations: FAHP analysis was conducted with 22 participants (10 senior fashion design experts and 12 designers from the experiments). While adequate for FAHP's mathematical requirements, a larger sample would enhance generalizability. FAHP's strength lies in handling the subjective ambiguity inherent in design decision-making and capturing nuanced trade-offs between competing priorities [32,33]. The pairwise comparison structure forces explicit trade-off judgments rather than independent ratings. However, findings should be regarded as exploratory. Future research should conduct larger-scale validation studies across diverse designer populations.

Four major dimensions and 16 specific factors were distilled from literature review and qualitative observations from the experiments. These factors formed an online questionnaire completed by 22 participants—10 senior experts in fashion design and engineering, and 12 designers from the experiments.

The FAHP was used to process the responses. FAHP was chosen for its ability to handle subjective ambiguity in decision-making. By constructing judgment matrices and calculating weights, it quantifies the relative importance of design factors. While traditional Analytic Hierarchy Process (AHP) is effective for decision-making relying on subjective judgment, its precise scales cannot fully capture ambiguity and uncertainty in expert opinions. FAHP, by incorporating fuzzy set theory, better reflects real-world situations. As demonstrated by Lee et al. [32] and Tian-xiang [33], FAHP is a powerful analytical tool in product design and complex system selection.

Ethical Considerations

This research was conducted in strict adherence to academic ethical norms. Given the involvement of marginalized demographics (elderly populations) and AI technology with potential for bias amplification, comprehensive ethical protocols were implemented across four dimensions:

- **Data Privacy and Informed Consent:** All participants were fully informed of the research purpose, methods, potential risks, and their rights prior to participation. Written informed consent was obtained, and strict anonymization and confidentiality protocols were implemented. For LoRA model training in Experiment 2, explicit consent was obtained from Ms. Chen regarding the use of her personal photos, with assurances of secure data handling and deletion after research completion.
- **Digital Exclusion Risks:** The framework, while intended to serve elderly populations, paradoxically requires technological infrastructure and literacy that may exclude many elderly individuals. Ms. Chen, as a university lecturer with high digital literacy, is not representative of the broader East Asian elderly population. Future research should explore intermediated models where designers or family members facilitate AIGC-based personalization for elderly individuals with limited digital literacy.
- **Algorithmic Discrimination Risks:** Hyper-personalization based on individual characteristics could reinforce stereotypes if not carefully implemented. For example, LoRA models trained on elderly individuals could consistently generate conservative or traditional styles, reinforcing ageist assumptions. This was mitigated by encouraging diverse style exploration and maintaining designer agency, but ongoing monitoring for emergent biases is recommended.
- **Long-term Ethical Implications:** AI-mediated identity representation raises questions about authenticity, consent boundaries, and potential misuse. While the research context was controlled and consensual, commercial deployment of such technologies raises concerns about deepfakes, unauthorized use of personal likenesses, and psychological impacts. Robust governance frameworks and ethical guidelines are necessary for AIGC applications in fashion and beyond.

Multiple measures were taken to reduce researcher bias, ensuring fairness, objectivity, and scientific integrity.

DATA COLLECTION AND EVALUATION

Derivation of Designer’s Key Consideration Factors

To address SQ2 (“What are the key factors designers prioritize when using AIGC?”), a comprehensive evaluation framework was constructed. Factors were systematically derived from literature review and qualitative data collected in the design experiments. In-depth interviews with participating designers captured specific concerns and challenges encountered in practical AIGC tool operation. Synthesizing theoretical and practical sources, four core dimensions and 16 specific consideration factors were identified

(Figure 23), laying the foundation for subsequent quantitative analysis.

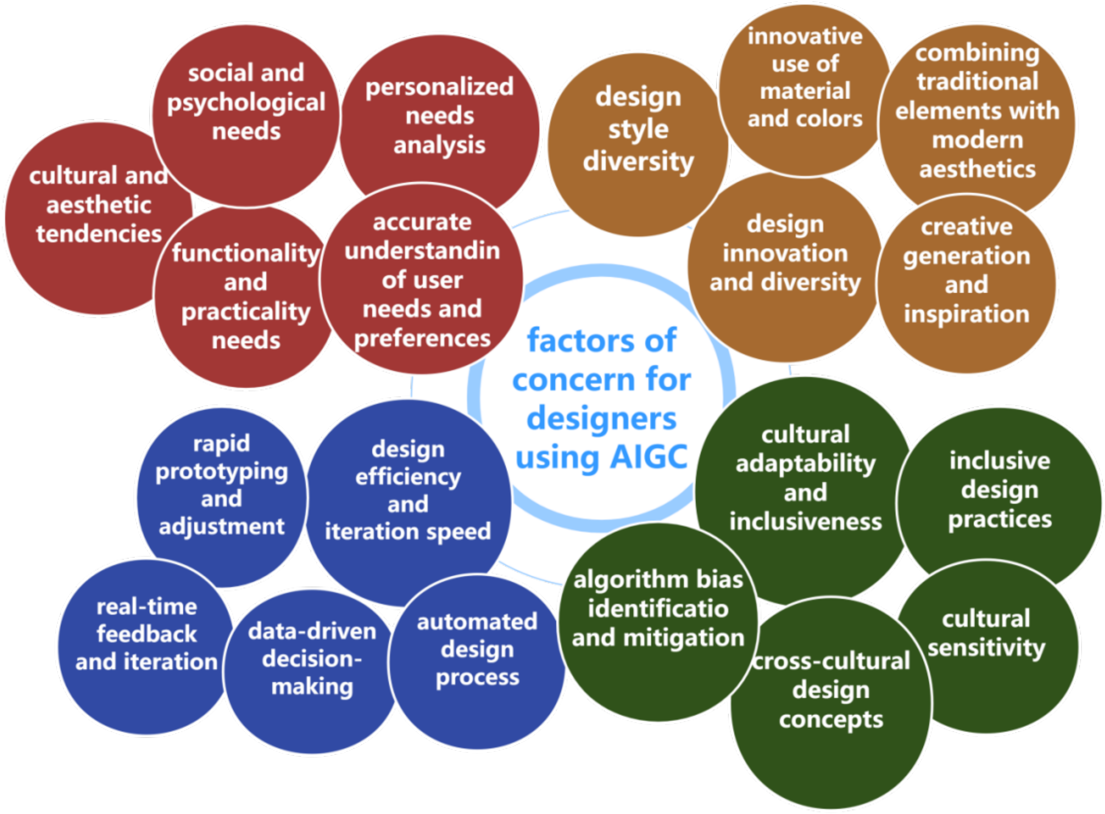

Figure 23. Key factors that designers focus on during the process of integrating AIGC, derived from literature review and qualitative feedback in Experiments 1 and 2

Research Method: Fuzzy Analytic Hierarchy Process (FAHP)

FAHP was used to process the 22 valid questionnaire responses. Unlike traditional AHP, FAHP incorporates fuzzy set theory to better handle subjective ambiguity in expert decision-making [32,33], making it suitable for quantifying nuanced aesthetic and functional trade-offs in fashion design.

The optimization process for analyzing design factors begins with the foundational mathematical theorem of the fuzzy matrix. An n-dimensional square matrix is defined, adhering to the criteria of a fuzzy complementary matrix, and consistent fuzzy matrix criteria, where matrix elements satisfy specific relational properties:

- $0 \leq r_{ij} \leq 1$, $(i, j = 1, 2, \ldots, n)$: R is a fuzzy matrix.
- $r_{ij} + r_{ji} = 1$, $(i, j = 1, 2, \ldots, n)$: R is a fuzzy complementary matrix.
- $r_{ii} = 0.5$, $r_{ij} = r_{ik} - r_{jk} + 0.5$, $(i, j, k = 1, 2, \ldots, n)$: R is a consistent fuzzy matrix.

To quantitatively assess the importance of various design factors, the fuzzy hierarchical analysis method constructs a scoring matrix using a 0.1–0.9 scaling method, with each score reflecting the relative importance of one factor over another [33]. The matrix is processed to derive the weights of each factor, followed by a consistency test to ensure reliable results (CI < 0.1 indicates consistency).

Due to strong subjectivity in expert scoring, inconsistencies or omissions often occur. Particle Swarm Optimization (PSO), developed by Dr. Eberhart and Dr. Kennedy in 1995, is utilized to rectify these issues. PSO, inspired by bird flocking behavior, guides the collective search for optimal solutions. Each particle updates its velocity and position according to established equations, with learning factors influencing trajectory and a maximum velocity limit imposed for controlled exploration.

FAHP Analysis Results

The 16 derived factors were converted into an online questionnaire and distributed to 22 participants, including 10 senior fashion design experts and 12 designers from the experiments. After obtaining consent, FAHP analysis was performed on the collected data. The calculated Consistency Index (CI) was 0.041, confirming reliability and logical consistency.

The analysis revealed significant differences in the degree of attention designers pay to various factors when using AIGC for East Asian elderly fashion design. Global and relative weights of all factors are summarized in Table 1, with Figure 24 providing a Bubble Chart visualization. “Design Efficiency and Iteration Speed” (global weight 0.3923) is the core dimension of greatest concern to designers, followed by “Design Innovation and Diversity” (0.2962), “Cultural Adaptability and Inclusiveness” (0.1628), and “Accurate Understanding of User Needs” (0.1486).

Table 1. FAHP Analysis Results of Design Factors in the Application of AIGC for Asian Elderly Fashion Design

Design Factors	Global Weight	Relative Weight
Accurate understanding of user needs and preferences	0.1486	-
Personalized needs analysis	0.0564	0.3792
Cultural and aesthetic tendencies	0.0293	0.1969
Functionality and practicality needs	0.0322	0.2167
Social and psychological needs	0.0308	0.2073
Design innovation and diversity	0.2962	-
Creative generation and inspiration	0.1240	0.4188
Design style diversity	0.0811	0.2740
Innovative use of materials and colors	0.0549	0.1854
Combining traditional elements with modern aesthetics	0.0361	0.1219
Design efficiency and iteration speed	0.3923	-
Rapid prototyping and adjustment	0.1602	0.4083
Automated design process	0.0981	0.2500
Data-driven decision-making	0.0445	0.1135

Real-time feedback and iteration	0.0895	0.2281
Cultural adaptability and inclusiveness	0.1628	-
Cultural sensitivity	0.0297	0.1823
Algorithm bias identification and mitigation	0.0404	0.2479
Cross-cultural design concepts	0.0312	0.1917
Inclusive design practices	0.0616	0.3781

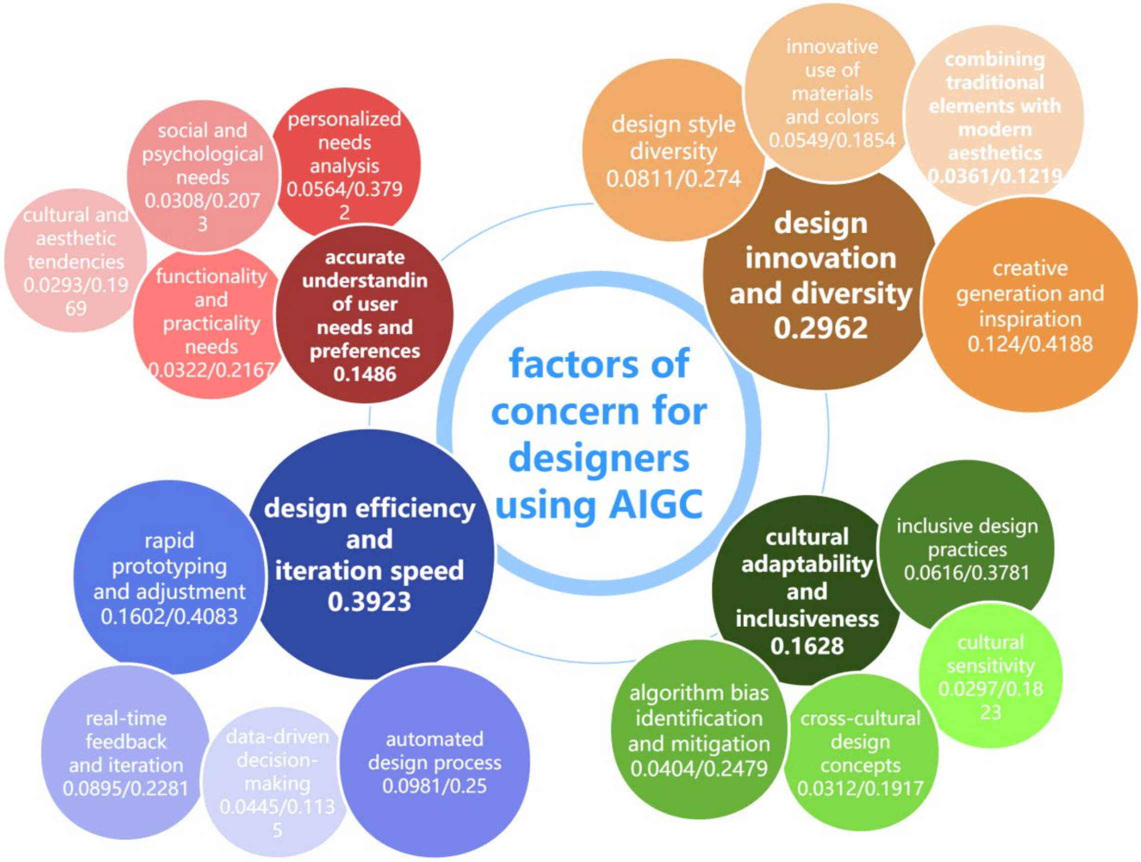

Figure 24. Bubble Chart visualization of the FAHP analysis data

DISCUSSION OF RESULTS

The FAHP results provide significant insights into designers' perceptions of AIGC, directly addressing SQ2 and aligning with decision-making models in engineering design [32]. Efficiency is the primary driver for designer adoption of AIGC, with "Design Efficiency and Iteration Speed" (global weight 0.3923) as the most important dimension. "Rapid prototyping and adjustment" (relative weight 0.4083) and "Automated design process" (0.2500) are particularly prominent, indicating that designers view AIGC as a powerful productivity tool that accelerates creative validation and iteration.

AIGC is also regarded as a catalyst for creativity, not a substitute. “Design Innovation and Diversity” is the second most important dimension, with “Creative Generation and Inspiration” (0.4188) having the highest weight within it. Designers expect AI to help break through existing thought patterns and explore diverse design styles (0.2740), gaining new sources of inspiration.

Interestingly, while the study’s context is “human-centered,” the weight for “Accurate Understanding of User Needs” is relatively low. This may reflect a practical reality: designers currently perceive AIGC as primarily empowering their own creativity rather than directly understanding users. They are more inclined to use AIGC to efficiently realize their creative ideas. However, within “Cultural Adaptability and Inclusiveness,” “Inclusive Design Practices” (0.3781) and “Algorithm Bias Identification and Mitigation” (0.2479) received high weights, indicating designers’ awareness of the ethical and practical importance of inclusivity and bias mitigation when using AIGC.

Scalability and Production Considerations

A critical practical challenge for our framework is scalability: How can highly personalized, LoRA-based fashion designs be efficiently produced and distributed for an economically diverse elderly market? Moving from a single-case study to broader implementation requires addressing several interconnected challenges.

Not all users require the same depth of personalization. A tiered approach could balance customization with production efficiency. Basic tier personalization might use demographic adjustments—adapting standard models for East Asian facial features and body proportions without individual LoRA training. Intermediate tier personalization could employ shared LoRA models trained on small groups with similar characteristics. Deep tier personalization, as demonstrated in Experiment 2, would be reserved for premium services or special needs cases. This structure allows broader market access while maintaining deep personalization when justified.

The digital nature of AIGC-generated designs offers advantages for on-demand manufacturing integration. Once a personalized design is approved, digital patterns can be transmitted directly to automated cutting systems, 3D knitting machines, or digital textile printing equipment, bypassing traditional batch production and enabling small-batch or single-unit production. Several fashion technology companies are developing such digital-to-physical pipelines, indicating technical feasibility.

Highly personalized fashion production carries higher costs than mass production, creating barriers for economically disadvantaged elderly individuals. Models to address this tension include subsidized personalization programs through government healthcare or social welfare systems, collaborative consumption enabling cost-sharing among users, and hybrid approaches using AIGC personalization for critical elements while employing standard components elsewhere. Each model presents trade-offs between accessibility and customization depth.

A modular approach offers another pathway to scalability. AIGC could generate personalized elements—

custom prints with culturally meaningful symbols, adjusted proportions for individual body types—combined with standardized base garments, enabling mass customization rather than mass production.

These scalability solutions require further research and development. Future studies should conduct cost-benefit analyses, pilot production runs, and market validation to determine practical and economic viability across market segments.

CONCLUSION AND RECOMMENDATIONS

Summary of Findings

This study explored the construction and application of a human-centered AIGC fashion design framework to address algorithmic bias and aesthetic convergence in mainstream AIGC applications, particularly for the often-overlooked East Asian (Chinese) elderly user group. Employing a mixed-methods approach that combined two design experiments and quantitative evaluation using FAHP, the study systematically answered predefined research questions and arrived at the following core conclusions:

- In response to SQ1 (applying personalization technology to mitigate representational algorithmic bias), Experiment 2 validated the effectiveness of LoRA technology in achieving deep personalization. Fine-tuning a model on a representative user's personal dataset enabled the generation of fashion designs highly consistent with her characteristics, cultural background, and unique aesthetic (e.g., "cyberpunk combined with Chinese elements"). User-centric, personalized model training is a viable technical pathway for overcoming biases such as the "Western Gaze" in mainstream AIGC models and achieving culturally inclusive design for East Asian (Chinese) elderly populations.
- Regarding SQ2 (key factors for designers using AIGC), FAHP analysis provided profound insights. Designers primarily view AIGC as a tool for enhancing "Design Efficiency and Iteration Speed" (global weight 0.3923), and secondarily as a source of inspiration for "Design Innovation and Diversity" (0.2962). The core value of AIGC is currently perceived as "empowering the designer." Designers also emphasized "Inclusive Design Practices" and "Algorithm Bias Identification," indicating awareness of ethical responsibilities in technology application.
- For SQ3 (the contribution of the AIGC framework to sustainable design), both experiments demonstrated the immense potential of digital prototyping in early design stages. Rapid generation of visual concepts with AIGC enables extensive creative exploration and concept screening without consuming physical materials, accelerating iteration and reducing material waste—aligning with Industry 5.0 sustainability requirements.

Main Contributions

The principal contribution is the proposal of an integrated, human-centered AIGC fashion design framework. This framework places the “human” (the user) at the center through deep personalization technologies (e.g., LoRA), while understanding and respecting the “human” (the designer) via quantitative analysis (e.g., FAHP) of creative habits and decision-making logic. The framework provides a practical method for addressing the inclusivity problem of AIGC and offers theoretical guidance for future human-computer collaboration in creative fields.

Limitations, Future Directions, and Recommendations

Several critical limitations shape our contributions and inform recommendations for researchers and practitioners:

- Findings regarding “Asian elderly” apply specifically to East Asian (Chinese) contexts. Asia’s vast cultural diversity means the framework’s effectiveness for other populations remains unvalidated. Future research must extend validation to other regions, with cultural adaptations as necessary [23].
- Methodologically, three limitations constrain generalizability: (1) Experiment 2 involved a single case (Ms. Chen, with high digital literacy), who is not representative of broader East Asian elderly populations; (2) FAHP analysis involved only 22 participants; (3) Bias mitigation was evaluated qualitatively rather than with quantitative metrics. Future research should include larger-scale user studies, expanded designer samples, and development of standardized bias evaluation metrics.
- Practically, sustainability claims rest on inference rather than measured evidence, and the framework culminated in a single personalized garment, not scalable production. Scaling personalized production for broader markets remains an open challenge.

Recommendations include:

- **For researchers:** Develop quantitative evaluation frameworks—bias metrics, lifecycle analyses—and validate scalability through pilot studies. Address accessibility by developing intermediated models for elderly individuals with limited digital literacy.
- **For industry practitioners:** Strategically adopt AIGC to enhance efficiency and creativity, build diverse datasets, implement tiered personalization approaches, and maintain human oversight for cultural sensitivity and bias mitigation.
- **For design educators:** Integrate AIGC tools and critical discussions on AI ethics, data bias, and algorithmic fairness into curricula. Emphasize technical proficiency and ethical judgment.
- **For policymakers:** Establish data privacy standards for personalized AI models, create accessibility programs to prevent digital exclusion, and support research into bias metrics for fashion AI applications. Recognize that culturally appropriate clothing contributes to elderly wellbeing,

potentially justifying public investment.

This study opens pathways for human-centered AIGC applications in fashion. Future research and practice must advance from demonstration to validation, from single cases to populations, and from technological capability to responsible deployment.

Author Contributions

Conceptualization – Hongcai Chen and Yan Wang; methodology – Vongphantuset Jirawat and Sirivesmas Veerawat; resources – Yongshun Che; writing-original draft preparation – Hongcai Chen; writing-review and editing – Yan Wang; visualization – Hongcai Chen; supervision – Yan Wang. All authors have read and agreed to the published version of the manuscript.

Conflicts of Interest

The authors declare no conflict of interest.

Funding

This study was supported by the Fujian Provincial Science and Technology Plan Project for Foreign Cooperation (No.2023I0040) "China-South Africa" Textile and Garment Digital Twin Collaborative Smart Manufacturing System Construction and Evaluation, and Fujian Provincial Science and Technology Project Innovation Fund Project, "Research and Development and Application of Intelligent Annotation System for Regional Characteristic Textiles and Clothing Based on Multimodal Learning" (No. 2025C01010017), Fujian Provincial Software Industry Technology Innovation Key Research and Industrialisation Project (Third Batch) - R&D and Industrialisation of AI Design Enabling Platform for Textile and Garment Industry.

Ethics Approval and Consent to Participate

This study was reviewed and approved by the Scientific Research Ethics Committee of the Fujian Digital Media Economy Research Center, Minjiang University (Date: [2024-12-14]). All participants provided informed consent for their involvement in the study. All methods were carried out in accordance with relevant guidelines and regulations.

Data Availability

The datasets used and/or analyzed during the current study, including the training data for the LoRA model and the data collected from surveys, are not published as supplementary material due to potential concerns regarding the portrait rights of the participants involved. However, they can be made available from the corresponding author on reasonable request.

Acknowledgements

The authors would like to express their gratitude to the editorial office for their thorough review and formatting assistance. We also thank Ms. Chen Hong for her valuable support during the research process.

REFERENCES

[1] Liu L, Zhang H, Ji Y, Wu QMJ. Toward AI fashion design: An attribute-GAN model for clothing match. Neurocomputing. 2019; 341:320–330. doi: 10.1016/j.neucom.2019.03.011

[2] Park K. Study on the feasibility of using AI image generation tool for fashion design development – focused on the use of Midjourney. The Journal of the Convergence on Culture Technology. 2023; 9(6):237–244. doi: 10.17703/JCCT.2023.9.6.237

[3] Kato N, Osone H, Sato D, Muramatsu N, Ochiai Y. DeepWear: A case study of collaborative design between human and artificial intelligence. In Proceedings of the Twelfth International Conference on Tangible, Embedded, and Embodied Interaction; 18–21 March 2018; Stockholm, Sweden. New York, NY, USA: Association for Computing Machinery; 2018. p. 529–536. doi: 10.1145/3173225.3173302

[4] Guo Z, Zhu Z, Li Y, Cao S, Chen H, Wang G. AI assisted fashion design: A review. IEEE Access. 2023; 11:74391–74406. doi: 10.1109/ACCESS.2023.3298850

[5] Giri C, Jain S, Zeng X, Bruniaux P. A detailed review of artificial intelligence applied in the fashion and apparel industry. IEEE Access. 2019; 7:95376–95396. doi: 10.1109/ACCESS.2019.2928979

[6] Huang Z, Li Y, Pei D, Zhou J, Ning X, Han J, et al. FIRST: A million-entry dataset for text-driven fashion synthesis and design. arXiv preprint. 2023; arXiv:2311.07414. doi: 10.48550/arXiv.2311.07414

[7] Vaccaro K, Agarwalla T, Shivakumar S, Kumar R. Designing the future of personal fashion. In Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems; 21 – 26 April 2018; Montreal, QC, Canada. New York, NY, USA: Association for Computing Machinery; 2018. p. 1–11. doi: 10.1145/3173574.3174201

[8] Gao J, Choo KTW, Cao J, Lee RKW, Perrault S. CoAIcoder: Examining the effectiveness of AI-assisted human-to-human collaboration in qualitative analysis. ACM Transactions on Computer-Human Interaction. 2023; 31(1):1–38. doi: 10.1145/3617362

[9] Ramos L, Rivas-Echeverría F, Pérez AG, Casas E. Artificial intelligence and sustainability in the fashion industry: A review from 2010 to 2022. SN Applied Sciences. 2023:5(12). doi: 10.1007/s42452-023-05587-2

[10] Seol J, Kim S, Park S, Lim H, Na H, Park E, et al. Technologies for AI-driven fashion social networking service with e-commerce. Semantic Intelligence: Select Proceedings of ISIC 2022; 2023:187-204. doi: 10.48550/arxiv.2203.10996

[11] Cao S, Chai W, Hao S, Zhang Y, Chen H, Wang G. Difffashion: Reference-based fashion design with structure-aware transfer by diffusion models. IEEE Transactions on Multimedia. 2023. doi: 10.48550/arxiv.2302.06826

[12] Li Q, Xue Z, Wu Y, Zeng X. The status quo and prospect of sustainable development of smart clothing. Sustainability. 2022; 14(2):990. doi: 10.3390/su14020990

[13] Chen P, Wu L, Wang L. AI fairness in data management and analytics: A review on challenges, methodologies and applications. Applied Sciences. 2023; 13(18):10258. doi: 10.3390/app131810258

[14] Anantrasirichai N, Bull D. Artificial intelligence in the creative industries: A review. Artificial Intelligence Review. 2022; 55:589–656. doi: 10.1007/s10462-021-10039-7

[15] Zhang Z, Zhao L, Yang T. Research on the application of artificial intelligence in image recognition technology. Journal of Physics: Conference Series. 2021; 1992(3):032118. doi: 10.1088/1742-6596/1992/3/032118

[16] Shi M, Chussid C, Yang P, Jia M, Dyk Lewis V, Cao W. The exploration of artificial intelligence application in fashion trend forecasting. Textile Research Journal. 2021; 91(19-20):2357-2386. doi: 10.1177/00405175211006212

[17] Noor A, Saeed MA, Ullah T, Uddin Z, Ullah Khan RMW. A review of artificial intelligence applications in apparel industry. The Journal of The Textile Institute. 2022; 113(3):505–514. doi: 10.1080/00405000.2021.1880088

[18] Chen HJ, Shuai HH, Cheng WH. A survey of artificial intelligence in fashion. IEEE Signal Processing Magazine. 2023; 40(3):64-73. doi: 10.1109/MSP.2022.3233449

[19] Huang YCJ, Wensveen SA, Funk M. Experiential speculation in vision-based AI design education: Designing conventional and progressive AI futures. International Journal of Design. 2023; 17(2):1-17. doi: 10.57698/v17i2.01

[20] Yin H, Zhang Z, Liu Y. The exploration of integrating the midjourney artificial intelligence generated content tool into design systems to direct designers towards future-oriented innovation. Systems. 2023; 11(12):566. doi: 10.3390/systems11120566

[21] Choi W, Jang S, Kim HY, Lee Y, Lee SG, Lee H, et al. Developing an AI-based automated fashion design system: Reflecting the work process of fashion designers. Fashion and Textiles. 2023; 10:39. doi: 10.1186/s40691-023-00360-w

[22] Kalpokas I. Work of art in the age of its AI reproduction. Philosophy Social Criticism. 2023; 49(7):1–19. doi: 10.1177/01914537231184490

[23] Fathers J, Bonsiepe G. Peripheral vision: An interview with Gui Bonsiepe charting a lifetime of commitment to design empowerment. Design Issues. 2003; 19(4):44–56. doi: 10.1162/074793603322545055

[24] Dubberly H. Gui Bonsiepe: Framing Design as Interface. The Disobedience of Design. Design Issues. 2022; 38(1):82–87. doi: 10.1162/desi_a_00674

[25] Adeshola I, Adepoju AP. The opportunities and challenges of ChatGPT in education. Interactive Learning Environments. 2024; 32(10):6159–6172. doi: 10.1080/10494820.2023.2253858

[26] Mccardle JR. The challenge of integrating AI & smart technology in design education. International Journal of Technology and Design Education. 2002; 12:59-76. doi: 10.1023/A:1013089404168

[27] Luckin R, Cukurova M. Designing educational technologies in the age of AI: A learning sciences-driven approach. British Journal of Educational Technology. 2019; 50(6):2824-2838. doi: 10.1111/bjet.12861

[28] Luo Y, Wang L. Crisis and responses to design and design education in the AIGC era. In Proceedings of the 4th International Conference on Education, Knowledge and Information Management (ICEKIM 2023); 26–28 May 2023; Nanjing, China. 2023. doi: 10.4108/eai.26-5-2023.2337328

[29] Gu R, Li H, Su C, Wu W. Innovative digital storytelling with AIGC: Exploration and discussion of recent advances. arXiv preprint. 2023. arXiv:2309.1429. doi: 10.48550/arXiv.2309.14329

[30] Zhang G. Construction of an AIGC-aided design course teaching and experiment base. Costume and Culture Studies. 2024; 2(4):28-43. doi: 10.6914/ccs.020404

[31] Mehrabi N, Morstatter F, Saxena N, Lerman K, Galstyan, A. A survey on bias and fairness in machine learning. ACM Computing Surveys. 2021; 54(6):1-35. doi: 10.1145/3457607

[32] Lee WB, Lau H, Liu Z-Z, Tam S. A fuzzy analytic hierarchy process approach in modular product design. Expert Systems. 2002; 18(1):32–42. doi: 10.1111/1468-0394.00153

[33] Dong-Chao J, Bifeng P, Tian-Xiang Y. FAHP and its application in the selection of design scheme. Systems Engineering and Electronics. 2006; 28. doi: 10.3321/j.issn:1001-506X.2006.11.022