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Development of an AI-driven branding platform integrating persona/scenario methods for fashion startups

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Abstract

As the fashion industry undergoes rapid digital transformation, designer brands have gained increasing visibility through expanded creative and communication opportunities. However, many still face significant challenges in brand development, including limited resources and insufficient consumer understanding. This study proposes an AI-driven branding framework that integrates the Persona/Scenario (P/S) methodology to assist designers in identifying visual style features, understanding target consumer profiles, and formulating strategic brand positioning. The framework incorporates multimodal AI components, including mixture-of-experts convolutional neural networks (MoE-CNNs) for visual style classification, large language models (LLMs) for consumer text analysis, and k-nearest neighbors (KNN) for brand similarity mapping in semantic space. Based on in-depth interviews and simulation-based evaluation procedures, the study demonstrates the potential of AI to enhance the traditional P/S approach and support brand strategy development for early-stage designer brands. The framework provides a scalable and flexible pathway to facilitate systematic and consumer-oriented brand growth. By proposing a structured yet adaptable decision-support system, this research contributes to the interdisciplinary integration of AI technologies and fashion branding and enables a strategic branding path that fuses user orientation with design-driven thinking.

Keywords: Fashion branding, Fashion startup, Persona/scenario method, AI-driven P/S platform, Consumer analysis, Style recommendation

Introduction

The fashion industry has shifted from emphasizing functional value to prioritizing brands that convey cultural meaning, identity, and emotional resonance (Arvidsson, 2006; Holt, 2004). Branding has accordingly become a strategic imperative, underpinning both market positioning and long-term viability (Kapferer, 2012; Keller, 2003). This transformation has spurred interest in designer-led niche brands, which center on creative authorship, aesthetic individuality, and culturally embedded narratives (Millspough & Kent, 2016; Yun & Choo, 2018), thereby contributing to greater innovation and stylistic diversity (Chell & Karataş-Özkan, 2014).

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Although designer-led fashion startups have gained growing academic and industry attention, their development remains constrained by structural limitations. Lacking robust data infrastructures and clearly defined target audiences (Gu, 2014), these brands often depend on intuition rather than systematic consumer insights (Ind & Watt, 2006; Jin & Cedrola, 2017). While branding theory is well established, most frameworks were designed for large, resource-rich enterprises and offer limited relevance to small-scale operations (Aaker, 2012; Fionda & Moore, 2009; Islam & Khan, 2013). Existing mass-market data and methodologies fail to capture the aesthetic complexity and narrative specificity central to designer branding (Peirson-Smith, 2013), frequently resulting in imprecise positioning, weak user alignment, and fragmented communication strategies.

Recent advances in artificial intelligence, especially deep learning, have enabled creative industries to automate pattern recognition, semantic analysis, and content generation at scale (Amin et al., 2025; Cetinic & She, 2022; Choi et al., 2019, 2023; Verganti et al., 2020). AI is increasingly applied in branding to align consumer preferences, analyze behavior, recognize styles, and construct narratives (Makosa, 2024; Yu et al., 2025), making data-driven strategies more accessible to fashion startups. However, current AI systems remain predominantly optimized for behaviorist, mass-market applications. Trained on large-scale datasets, these models excel in generic classification, user modeling, and recommendation tasks (Chen et al., 2019; Liu et al., 2016), but fall short in capturing the nuanced aesthetics, cultural semantics, and brand storytelling central to designer-led branding. More importantly, they lack structured methods for interpreting user intent, contextual significance, and brand value logic.

In this context, the Persona/Scenario (P/S) methodology offers a promising complementary approach. Grounded in user-centered design, P/S constructs archetypal user profiles and contextual narratives to guide strategic and creative decisions (Pruitt & Grudin, 2003; Visser et al., 2005). Its applications in fashion point to its potential for deepening user empathy and enhancing narrative coherence (Pruitt & Adlin, 2010).

When integrated into AI systems, P/S methods introduce a semantically rich input layer and contextual logic that support interpretability and simulation. This hybrid approach enables AI to move beyond task execution toward strategic co-creation—producing outputs that are not only context-sensitive but also strategically aligned (Goel et al., 2023; Lee & Lee, 2023; Salminen et al., 2021). Nonetheless, the application of AI-driven P/S frameworks in early-stage fashion branding remains underexplored.

Therefore, this study aimed to identify the early-stage branding challenges faced by startup fashion designers and, based on these insights, to develop an AI-driven P/S branding framework to support successful brand development. Based on this context, this study addresses the following research questions:

- (1) What branding challenges do fashion startups face?
- (2) How can AI-integrated Persona/Scenario methods be applied to structure a branding platform for fashion startups?
- (3) What distinctive values does an AI-driven branding platform integrating Persona/Scenario methods offer to fashion startups?

The research first investigated these challenges through literature review and in-depth interviews, followed by thematic analysis to extract key insights. Based on the findings, an AI-P/S branding platform was designed and developed, and its feasibility and practical value were evaluated through expert assessment. This study not only introduces a user-centered framework for intelligent branding but also provides theoretical grounding for the design of AI-assisted applications, the construction of integrated AI platforms in fashion, and the strategic enablement of startup fashion enterprises.

Literature Review

Branding process of fashion startups

Fashion brands serve as a critical component of contemporary consumer culture, offering not only functional products but also symbolic value through creative design and brand identity (Lee & Jeong, 2013). Within this domain, startup fashion designer brands represent a distinct category characterized by small-scale entrepreneurship, aesthetic originality, and responsiveness to emerging socio-cultural and technological trends. These brands often combine creative experimentation with agile business models, aiming to introduce innovative products or services that reflect their distinct visions (Park, 2024; Yun & Choo, 2018).

Driven typically by the founding designers themselves, these brands are operated with a compact structure, allowing for more consistent and flexible decision-making processes (Uh & Ha, 2020). Compared to mainstream fashion labels, startup designer brands emphasize conveying the designer's personal values, aesthetics, and worldview through brand identity. In this context, startups are seen as entrepreneurial ventures creating new value through a fusion of creativity and originality (Timmons & Spinelli, 1994), often consisting of individuals or small teams developing distinctive apparel collections that reflect a unique style or conceptual direction (British Fashion Council, 2024).

Branding is generally defined as the strategic process of creating and managing a unique identity to distinguish a product or service in the marketplace (Webster & Keller, 2004). This encompasses core elements such as brand identity, brand image, and brand positioning. As a critical strategy for achieving competitive advantage and long-term value, branding has been extensively modeled in the literature (Davis, 2002; Keller, 2008; King, 1991; Kotler & Keller, 2016; Kotler, Pfoertsch & Michi, 2006). In the context of Small and Medium-sized Enterprises (SMEs), Centeno et al. (2013) proposed a five-phase branding model emphasizing symbolic value, organizational identity, and market differentiation. Spence and Essoussi (2010) developed a founder-driven, value-oriented six-stage branding path, while Molin and Fredrikson (2011) outlined a four-phase digital branding framework integrating online platforms and real-time analytics to address dynamic consumer interactions. Although these frameworks vary in emphasis, they converge on a core branding trajectory comprising six stages: brand foundation, brand identity formation, brand positioning, brand differentiation, brand communication, and brand evaluation and growth. This sequence forms a comprehensive roadmap for developing and managing brand equity, as shown in Fig. 1.

However, for startup fashion designer brands, the branding process necessitates greater flexibility and frequently revolves around efficient resource allocation and

The process of brand branding							
	Researcher	step 1	step 2	step 3	Step4	step 5	Step6
general enterprises	King (1991)	Brand audit	Brand positioning/Brand personality	Brand strategy	Briefing		
	Davis (2002)	Brand value/ Brand image/Creating brand contract	Brand-based customer model/ Positioning the brand	Extending the brand	Communicating brand's positioning/ Leveraging the brand	Pricing the brand/Measuring return on brand investment	Establishing a brand-based culture
	Kotler, Pfoertsch & Michl (2006)	Brand planning(organizational framework)	Brand analysis(external internal)	Brand strategy(architecture target market)	Brand building/marketing plan implementation	Brand audit(controlling monitoring)	
	Keller (2008)	Brand identity	Brand Meaning		Brand Response		Brand Resonance
	Kotler & Keller (2016)	Brand purpose	Brand positioning	Brand differentiation	Brand identity	Brand trust	Brand beneficence
	Melin & Fredrikson (2011)	Product attributes	Brand identity	Positioning	Marketing communication		Distribution
Small and Medium-sized Enterprises	Centono, Hart & Dinnie (2013)	Brand as a person/ Brand as a product		Brand differentiation	Brand as a symbol	Brand as a organization	Brand identity development
	Spence & Esoussi (2010)	Brand "culture"	Brand identity	Brand equity	Brand strategy	Organization structure	Marketing mix

Fig. 1 Steps of the branding process

strategic differentiation. Unlike established fashion firms, startup designers face unique challenges rooted in their creative-driven identity and limited resources. As Mills (2011) notes, designers often excel in aesthetic execution but lack expertise in strategic planning and brand systemization. Consequently, branding for designers relies heavily on symbolic meaning and aesthetic articulation (Karra et al., 2008; Power & Hauge, 2008), yet often lacks the consumer insights and market analysis required for effective positioning (Gu, 2014). Additionally, resource constraints limit the capacity to sustain competitive communication strategies and consistent brand messaging (Aakko & Niinimäki, 2018; Stokes, 2000). These constraints can hinder the long-term scalability and visibility of designer-led ventures, especially when they attempt to expand beyond niche markets.

This study addresses these gaps by focusing on the branding processes of startup fashion designer brands, with the aim of developing a structured support mechanism that facilitates alignment between creative intent and strategic execution.

Application of P/S methods in fashion

The term persona, originating from the Greek word for “mask,” refers to a fictional yet data-informed representation of a target user group. Personas are widely adopted in user-centered design (UCD) to synthesize user insights into coherent profiles that communicate goals, frustrations, values, and behaviors of potential consumers (Cooper, 1999; Jansen et al., 2022; Miaskiewicz & Kozar, 2011). Initially developed to foster empathy among designers, personas have since evolved into a communication and decision-making tool in multidisciplinary teams, gaining traction across domains including software, marketing, healthcare, and service design (Adlin & Pruitt, 2010; Gudjonsdottir, 2010).

Complementary to personas, scenarios depict goal-oriented interactions between a persona and a system or service within a specific context. By visualizing how products will be used in real-world situations, scenarios bridge abstract user needs and practical design implications (Goodwin, 2009; Grudin & Pruitt, 2002). They are particularly effective in illustrating the emotional and behavioral dynamics that unfold throughout the consumer experience, and they support iterative design by offering a structured narrative to guide both concept generation and usability testing.

Within the fashion domain, the P/S methodology has drawn increasing attention for its potential to inform design direction, consumer engagement strategies, and inclusive practices. Ye and Yim (2015) explored designer personas in fashion marketing, highlighting the strategic importance of user-type classification in campaign design. Kim and Ha

(2017) identified three core persona typologies specific to the fashion field—avoidant, interpretive, and suppressive/explosive types—each corresponding to distinct decision-making processes of fashion designers. More recently, Shin et al. (2023) conducted a comprehensive analysis of persona implementation in fashion design, confirming its use across various stages including ideation, design planning, promotional storytelling, and consumer communication. In parallel, Lee et al. (2024) developed an educational toolkit to foster inclusive design thinking by integrating persona modeling as a pedagogical framework.

Despite its increasing application in fashion, the use of P/S methods in early-stage branding for startup fashion designer brands remains underexplored. This study addresses this gap by proposing a P/S-driven branding support model tailored for startup fashion designer brands. By combining consumer segmentation with scenario-based brand storytelling, the framework enables designers to construct differentiated brand identities, simulate user-brand interactions, and generate data-informed communication strategies.

AI-supported P/S methods

The P/S method can be constructed through a variety of theoretical perspectives, including the goal-directed approach (Cooper et al., 2014), role-based modeling (Pruitt & Grudin, 2003), the engaging perspective (Nielsen, 2019), and fiction-based constructions (Nielsen, 2013). While the P/S method has demonstrated significant value in user-centered design by facilitating empathetic understanding and design alignment, conventional development processes are often hindered by issues of limited scalability, subjective bias, and high resource demands (Marsden & Haag, 2016). In response to these limitations, recent advances in artificial intelligence, particularly in natural language processing and generative modeling, have introduced new possibilities for automating and expanding P/S approaches with greater accuracy and efficiency.

AI-supported P/S approaches integrate machine learning to generate dynamic, data-informed personas and scenarios. Early applications of segmentation using clustering algorithms (Mulder & Yaar, 2006; Pruitt & Grudin, 2003) have evolved into more sophisticated generative systems. For instance, Salminen et al. (2018) demonstrated the feasibility of generating personas using unsupervised techniques based on user-generated content. In the healthcare field, Alsaadi and Alahmadi (2021) proposed AI-generated patient personas to facilitate personalized treatment design, while Lampezhnev et al., (2021) employed generative models to derive psychological traits from social media data. Karimova (2025) highlighted the value of incorporating psychological theory and narrative into AI persona creation. Salminen et al. (2024) and Wang et al. (2024) further emphasized the role of large language models (LLMs) in extracting deeper user characteristics from embedding space representations.

Beyond persona generation, recent studies have integrated AI in scenario modeling to improve interpretability and context sensitivity. Fergnani (2019) proposed scenario-based persona generation frameworks that reveal how user roles adapt across different design situations. Similarly, Liang et al. (2024) highlighted the utility of combining behavioral analytics with generative AI to enable real-time persona adjustment based on feedback loops and evolving user needs. In e-commerce, Chen et al. (2024)

illustrated how AI-generated buyer personas can inform tailored recommendation and marketing strategies.

As generative AI continues to evolve, its integration with P/S methodology promises not only efficiency gains but also increased precision and contextual richness. For startup fashion designer brands, this technological convergence allows for rapid user profiling and scenario simulation, aligning branding strategies with real-time consumer dynamics and enabling data-driven creative decision-making.

AI in fashion

The continuous advancement of AI has profoundly reshaped the fashion industry across its entire value chain—from product design and manufacturing to marketing, retail, and customer experience (Guo et al., 2023; Makridakis, 2017; Wu & Li, 2025). Techniques such as computer vision, deep learning, and natural language processing are increasingly applied to tasks including visual recognition, fashion image analysis, trend forecasting, generative design, personalized recommendation systems, and virtual try-on services (Giri et al., 2019; Mohammadi & Kalhor, 2021; Park et al., 2025). These applications provide fashion designers with actionable insights and creative support, streamlining workflows and enhancing innovation.

Given the multifaceted nature of fashion-related tasks, diverse AI models are often required to achieve optimal outcomes across different objectives. Deep CNNs are widely used for visual tasks such as style classification and segmentation, while generative adversarial networks (GANs) support automated design synthesis. Transformer-based architectures and attention mechanisms—alongside LLMs—are increasingly utilized in multimodal representation learning, trend prediction, and consumer behavior modeling. These models are strategically aligned with task-specific objectives to ensure both accuracy and scalability in real-world applications (Kang et al., 2024; Kouslis et al., 2024; Shen et al., 2024).

The foundation of effective AI deployment lies in robust and domain-specific datasets. Contemporary fashion datasets typically include large-scale annotated images, garment types, brand labels, style attributes, pose estimation, and consumer interaction logs (Guo et al., 2023). Many of these datasets are inherently multimodal and multitask, supporting a wide range of use cases including trend analysis, product recommendation, virtual clothing generation, and customer profiling (An et al., 2023; Zou & Wong, 2021). The granularity and reliability of such datasets are critical for training AI systems capable of generating meaningful outputs within the fluid landscape of fashion.

Despite the increasing adoption of AI in mainstream fashion workflows, its applications in supporting early-stage designer-led brands remain underexplored. As fashion branding becomes increasingly consumer-driven and data-intensive, integrating AI with methods such as the P/S approach offers a structured yet adaptive framework for startup fashion designer brands. This integration enables designers to develop a more nuanced understanding of their target users, simulate realistic brand-consumer interactions, and make evidence-based decisions regarding brand identity, positioning, and communication strategies.

Methods

This study aims to develop an AI-assisted branding tool that supports fashion designer brands in navigating the complexities of brand building in an increasingly data-driven and consumer-oriented market. The research methodology is structured into three key phases: (1) in-depth interviews to identify branding processes and challenges faced by startup fashion designer brands; (2) the design of an AI-driven branding platform based on the P/S methodology; and (3) the evaluation of the proposed branding process through usability testing.

In-depth interviews

The first phase employed qualitative, semi-structured interviews to explore how fashion designers manage the processes of brand foundation, positioning, strategic planning, creative communication, and market expansion. The interview protocol was developed based on a six-stage branding framework that includes: brand foundation, brand identity, positioning, differentiation, communication strategy, and brand growth evaluation.

A total of 10 fashion designers with recognized market presence and experience were selected as participants, including six Chinese and four Korean designers. Their brands are featured on prominent digital platforms such as Musinsa (2024) and Xiaohongshu (2024), ensuring cross-cultural and industry relevance. The selected brands represent various stages of development—from initial launch to growth and expansion—providing a comprehensive perspective on the evolving challenges of brand building, as shown in Table 1.

Each interview was conducted via Zoom and lasted approximately 90 min. All interviews were recorded and transcribed for thematic analysis following Braun and Clarke’s (2006) methodology. Thematic analysis proceeded through three major coding stages: open coding, axial coding, and selective coding. NVivo 12 software was used to facilitate the analysis. To ensure inter-coder reliability, two researchers independently coded the data. A random 20% sample of the coded data was assessed using SPSS, yielding a Cronbach’s alpha of 0.84. Any discrepancies were resolved through discussion and consensus.

AI-driven P/S branding platform design and evaluation

This phase of the study aimed to develop and evaluate an AI-driven P/S Branding Platform designed to assist fashion designers in establishing their brands through a structured, data-informed, and user-centered workflow. The platform’s conceptual framework was grounded in insights derived from in-depth interviews and was

Table 1 Interviewee’s profiles

Interviewee Code	Nationality	Brand Establishment Year	Interviewee code	Nationality	Brand establishment year
Designer 1	South Korea	2013	Designer 6	China	2017
Designer 2	South Korea	2017	Designer 7	China	2019
Designer3	South Korea	2015	Designer 8	China	2020
Designer 4	South Korea	2019	Designer 9	China	2022
Designer 5	China	2015	Designer 10	China	2023

architected as a modular system encompassing five core functional components: (1) designer style recognition, (2) market environment analysis, (3) user persona recommendation and generation, (4) scenario generation, and (5) strategic suggestions.

To support this workflow, the internal architecture of the AI platform was structured around two core components: data infrastructure and model architecture. The data infrastructure comprised the collection and organization of three main data types—design data, market data, and user data. Design data consist of fashion product images annotated with multi-label style tags. The dataset includes 29,871 images collected from 70 representative designer brands from China and South Korea, sourced from platforms such as Musinsa (2024), W Concept (2024), Xiaohongshu (2024), and Taobao (2024), covering collections from 2024 to 2025. Style annotations were manually labeled by five fashion design researchers based on industry trend reports and mainstream fashion classification systems, ensuring both consistency and professional relevance. Market data were collected from a range of industry reports published by leading institutions such as Boston Consulting Group and Fashion for Good (2025), CBNDData (2025a, 2025b, 2025c, 2025d), Lu (2025), Marketcast (2024), and JLL (2024), as well as online fashion trend analyses by authors such as Hwang and Salessy (2025), Kyndof (2024), in order to identify generational shifts in fashion consumption and to contextualize the environmental assessment within real-world market dynamics. In addition, user data were constructed by integrating structured survey responses with behavioral insights extracted from social media platforms, thereby supporting the generation of persona clusters and scenario simulations.

Regarding the model architecture, AI models were aligned with each stage of the branding process. A suite of integrated models, including MoE-CNNs, KNN, and DeepSeek-VL, was proposed to facilitate style recognition, multimodal matching between visual design elements and user persona profiles, and context-specific scenario generation.

Among them, the MoE-CNN differs from traditional CNNs in that it uses a gating mechanism to assign input samples to different expert subnetworks. Each expert focuses on specific fashion style attributes such as color, pattern, silhouette, and aesthetic orientation. This structure is particularly effective for fashion startups, whose garments often present hybrid styles combining diverse visual elements. The MoE-CNN allows for multi-label classification and better captures the complexity and diversity of designer brand styles.

As shown in Fig. 2, input garment images are first segmented using SAM2-based image segmentation. The segmented outputs are then processed by the MoE-CNN, where different experts extract visual attributes. The gating mechanism dynamically routes data to different towers, each predicting one style tag. The resulting multi-label style vector is used for brand classification and style-to-brand matching.

Next, the KNN model calculates semantic similarity between the generated style vector and user persona embeddings, helping identify the most relevant personas for each design. DeepSeek-VL is then used to simulate P/S and generate branding suggestions based on input. These models collectively enabled the construction of a AI-driven P/S branding platform tailored to the needs of startup fashion designer brands.

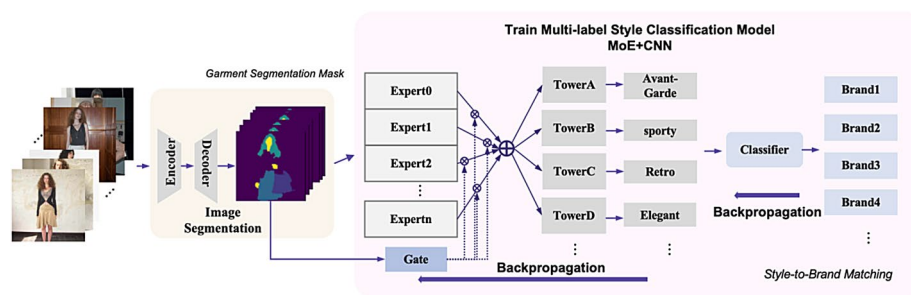


Fig. 2 Architecture of the MoE-CNN-based multi-label fashion style classification and brand matching model

Usability test

To assess the effectiveness of the proposed platform design, usability testing was conducted with five fashion designers who had previously participated in the initial interview phase. The purpose of evaluation was to examine the feasibility and usability of each functional module and procedural stage within the simulated branding workflow. During the testing process, participants first reviewed the entire AI-supported branding framework developed for fashion startups. Subsequently, they completed a structured questionnaire designed to assess the feasibility of the proposed workflow.

The questionnaire was constructed based on the Technology Acceptance Model (TAM) (Davis, 1989), measuring three key constructs in the context of an AI-driven P/S Branding Platform: Perceived Usefulness (PU), Perceived Ease of Use (PEOU), and Behavioral Intention (BI). To capture nuanced aspects of user experience, empirically validated sub-dimensions were integrated. Specifically, PU was assessed through result demonstrability, job relevance, and output quality. PEOU was extended to include perceived enjoyment and computer self-efficacy. These sub-dimensions were derived from TAM2 (Venkatesh & Davis, 2000) and related theoretical advancements (Compeau & Higgins, 1995; Davis et al., 1992), offering a robust framework for interpreting user responses to complex, task-oriented digital tools. Additionally, open-ended questions were included to gather qualitative feedback on the platform's strengths and areas for improvement. The collected data were then analyzed to refine the platform design and inform future enhancements.

Results

Thematic analysis of in-depth interviews

To explore the branding processes and challenges faced by startup fashion designer brands, ten semi-structured interviews were conducted with emerging designers. The interview transcripts were analyzed using thematic coding, resulting in 1,719 individual codes, which were clustered into 177 initial categories. These were further grouped into 45 subcategories, ultimately forming 10 core themes. These findings provide empirical grounding for the development of the AI-driven P/S Branding Platform proposed in this study, as shown in Figs. 3 and 4.

Theme 1: Motivations for Brand Creation (n = 113).



Fig. 3 Thematic coding map of designer brand development interviews

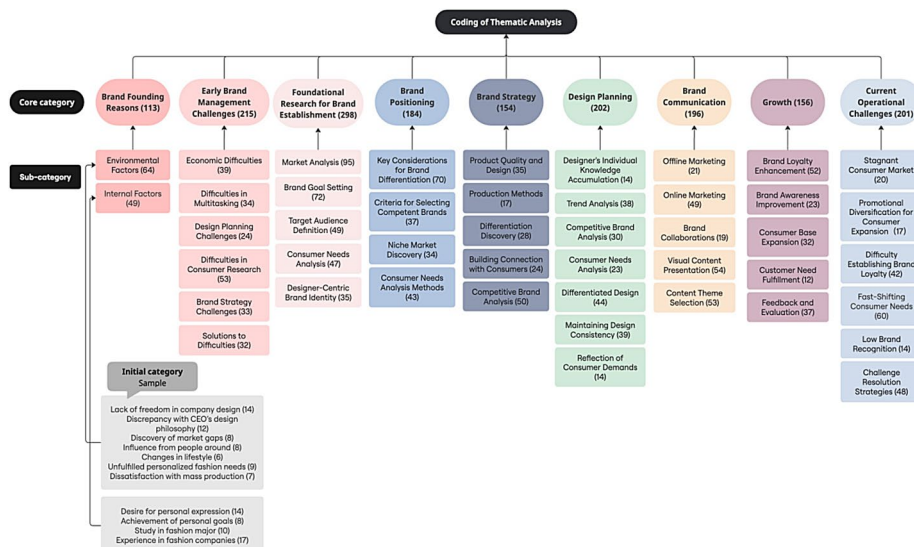


Fig. 4 Coding of thematic analysis with sample participant quotes

Participants articulated a desire to escape rigid hierarchical structures and creatively constraining corporate settings. External motivators included misalignment with managerial philosophies, limited creative freedom, and unaddressed market gaps.

As Designer 2 explained,

"In the company, I could only create what the boss liked, but I didn't like those things

myself.”

Internally, motivations such as self-actualization, professional autonomy, and confidence—often cultivated through formal education or prior work experience—were frequently cited as the foundation for initiating independent brand ventures.

As Designer 3 noted,

“I majored in fashion, and I’ve worked for years in a brand company—I know the market and what customers like very well.”

Together, these external and internal factors formed a strong foundation for initiating a designer-led brand.

Theme 2: Early Brand Management Challenges (n = 215).

Early-stage difficulties were consistently reported across interviews, including financial limitations, insufficient marketing resources, and difficulty accessing investors or institutional support.

As Designer 4 explained,

“Our budget is small, so it’s difficult to promote the brand and let people know we exist.”

Many also struggled with consumer research, lacking the tools and data to conduct structured analysis. They relied on informal feedback, often resulting in a disconnect between intended and actual consumers.

Operational overload further hindered progress. Managing design, marketing, and logistics alone left little time for creative work, slowing production cycles and reducing market responsiveness.

Theme 3: Pre-brand Research and Intuition-driven Planning (n = 298).

Due to financial constraints, formal market research was rarely undertaken. Instead, most participants relied on self-reflective evaluations of personal aesthetic strengths and internal capabilities.

As Designer 6 shared,

“I didn’t have the means to do full market research, so I mostly relied on my past experience and what I personally felt was missing in the market.”

Designers rarely set measurable goals, instead defining brand objectives through creative identity and cultural values. Target audiences were often based on personal networks rather than data, leading to vague positioning and reliance on post-launch feedback. In contrast, competitor analysis—via peer observation on platforms like Instagram or W Concept—served as a primary research method in the absence of structured tools.

Theme 4: Brand Positioning (n = 184).

Designers prioritized distinctiveness over price or scale, emphasizing style, philosophy, and consumer identity as core brand assets. Perceived value was anchored in design originality, material quality, and conceptual coherence—legitimizing premium pricing as an expression of artistic integrity.

To refine positioning, many employed competitive benchmarking, targeting brands with similar aesthetics or values. Designers also focused on niche audiences tied to subcultures, value-driven communities, or emerging style segments. By monitoring

visual trends, consumer feedback, and adjacent brand communities, they aimed to cultivate authentic emotional resonance with underserved consumer groups.

Theme 5: Strategic Brand Development (n = 154).

Designers consistently framed their brand strategies around preserving a distinctive design language and high-quality craftsmanship, while actively navigating the tension between creative originality and market wearability.

Resource constraints shaped operational choices, with small-batch production and pre-order systems emerging as recurring practices to manage inventory and stabilize cash flow. Emotional storytelling also featured prominently in the coding, as designers described embedding personal or cultural narratives to build deeper consumer resonance.

As Designer 7 noted,

“What people buy isn’t just clothing, but the concept behind it—the story, the message.”

Competitor monitoring remained a practical tool for strategic adjustment, with designers observing other independent brands’ pricing, content, and release cycles to remain responsive within a rapidly shifting market.

Theme 6: Design Planning (n = 202).

Designers described their planning process as a synthesis of personal experience, targeted trend adaptation, competitor analysis, and consistent brand expression. Highlighting how lived experience served as a primary creative driver and source of emotional depth. Designers engaged with trend information selectively, prioritizing alignment with brand identity over seasonal conformity. Competitive benchmarking—particularly analysis of best-selling items—was used to refine silhouettes and color strategies, enhancing market responsiveness.

Maintaining a stable brand language remained essential.

“I want customers to immediately recognize my work, even if the inspiration changes each season,” said one designer 3.

Over time, consumer feedback became increasingly influential, anchoring creative decisions within real market responses.

Theme 7: Brand Communication (n = 196).

At the brand communication stage, designers aimed to strengthen engagement, emotional resonance, and identity consistency. Offline tactics such as pop-ups and multi-brand spaces were employed to create immersive, experience-driven touchpoints. Digital communication was described as indispensable, with designers relying on social media, livestreaming, and targeted communities to build visibility and loyalty.

One designer 7 explained,

“We created a private space for fans to test ideas—it builds trust more easily.”

Visual storytelling emphasized consistent tone across platforms, using unified photography, modeling, and narratives. Collaborations with influencers or like-minded brands were employed to extend cultural reach and reinforce identity. However,

limited digital marketing expertise and resource constraints often hindered effective consumer engagement.

Theme 8: Brand Growth and Customer Retention (n = 156).

To foster consumer loyalty, designers implemented personalized services, built brand communities, and maintained post-purchase engagement. Many expanded reach through audience segmentation and fan-based platforms, encouraging organic diffusion. However, most lacked the capacity to conduct systematic data analysis, limiting their ability to assess the effectiveness of these strategies.

To stay relevant, designers relied on informal methods—monitoring reviews, social media, and direct messages—to adjust design and messaging. While this feedback loop offered valuable insights, the absence of structured analytic tools made it difficult to translate feedback into long-term strategic planning.

Theme 9: Current Operational Challenges (n = 201).

Designers at varying stages reported distinct operational challenges. For early-stage brands, economic stagnation, resource limitations, and weak marketing capacity were central concerns.

As Designer 7 explained,

“Ads are expensive, and even if they’re good, they don’t always lead to sales.”

Despite broader visibility via social media, many noted a disconnect between exposure and conversion, often due to limited communication expertise.

In the maintenance stage, sustaining consumer loyalty proved difficult amid trend saturation and shifting preferences.

Across all stages, accelerated trend cycles and rising competition required high responsiveness and adaptability. These pressures intensified in the expansion phase, where low awareness in new markets demanded strategic investment in branding and consumer education.

AI role supporting brand establishment

Building on the interview findings, the branding journey of startup fashion designer brands was reorganized into five key stages: pre-branding, brand initiation, brand growth, brand maintenance, and brand expansion, as shown in Fig. 5. Each stage was analyzed to identify design tasks, pain points, and existing workaround strategies. The Pre-Brand Establishment stage primarily encompasses foundational market and

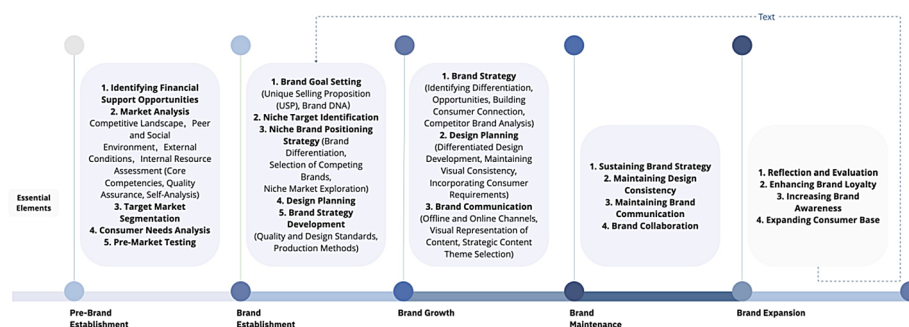


Fig. 5 Strategic phases and key elements in the fashion brand development lifecycle

economic analyses, consumer needs assessment, and preliminary product validation through market testing. Subsequently, the Brand Establishment phase involves strategic activities such as setting brand objectives, defining brand identity, delineating target audiences, differentiating from competitors, and positioning within the marketplace.

In the Brand Growth stage, emphasis shifts toward refinement of brand differentiation, enhancement of consumer engagement, competitive analysis, exploration of niche market opportunities, and iterative design planning, coupled with quality assurance and production optimization. The Brand Maintenance phase focuses on sustaining brand coherence through design consistency, strategic brand management, and robust communication with consumers. Finally, the Brand Expansion phase addresses growth-oriented objectives including strengthening brand loyalty, broadening consumer demographics, continuous evaluation and reflection, and strategic collaborations to foster brand scalability, as shown in Fig. 6.

Based on this, AI-enabled support opportunities were identified across four strategic domains: consumer understanding, brand decision-making, creative assistance, and brand communication, as shown in Fig. 7. AI can generate accurate, dynamic user profiles by integrating behavioral, demographic, and psychographic data. This enables evidence-based insight into evolving consumer needs and aesthetic preferences, moving beyond reliance on designer intuition. Through data-driven insights derived from large-scale fashion datasets, AI can support brand ideation, niche identification, and positioning. Functions include trend forecasting, market segmentation, and persona generation. Localized brand strategies are enhanced through competitive landscape mapping and regional market profiling. Generative AI and multimodal models enable designers to conceptualize and visualize design ideas grounded in user personas and contextual scenarios. Scenario-based user-product interaction simulations help predict consumer responses, improving product-market fit. Visual consistency across collections is maintained via automated style analysis. AI facilitates personalized marketing and multi-channel content delivery. Scenario-based prompts enable designers to tailor messaging that resonates with consumer motivations and expectations, thereby enhancing storytelling and promotional effectiveness.

Workflow design using AI-driven P/S method

To systematically support the early-stage brand development of startup fashion designer brands, this study proposes a structured branding workflow grounded in an AI-driven P/S method. The architecture of this workflow provides strategic guidance from the initial brand ideation phase through establishment, growth, and expansion, ensuring that each step is informed by iterative data and persona-driven insights, as shown in Fig. 8.

Pre-branding phase: design identity and market understanding

In the preparatory stage, designers conduct preliminary market research and define their design identity. This includes identifying core aesthetic attributes and analyzing stylistic positioning and similar brands. These activities are supported by the platform's initial input interface, which helps clarify the designer's aesthetic direction and highlights niche opportunities through data-informed visualization and trend comparison.

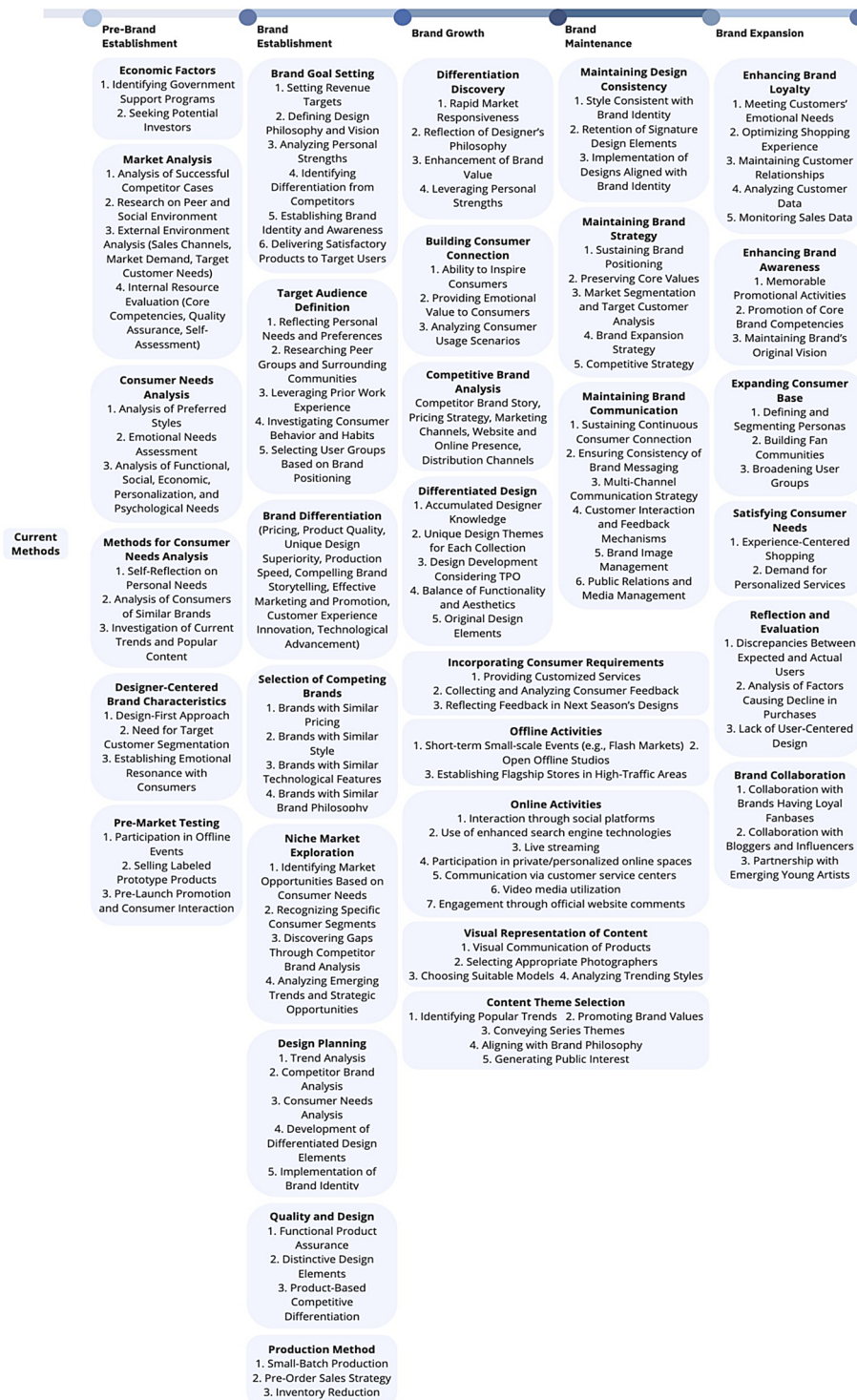


Fig. 6 Interview analysis results of key stages and strategies in fashion startup branding

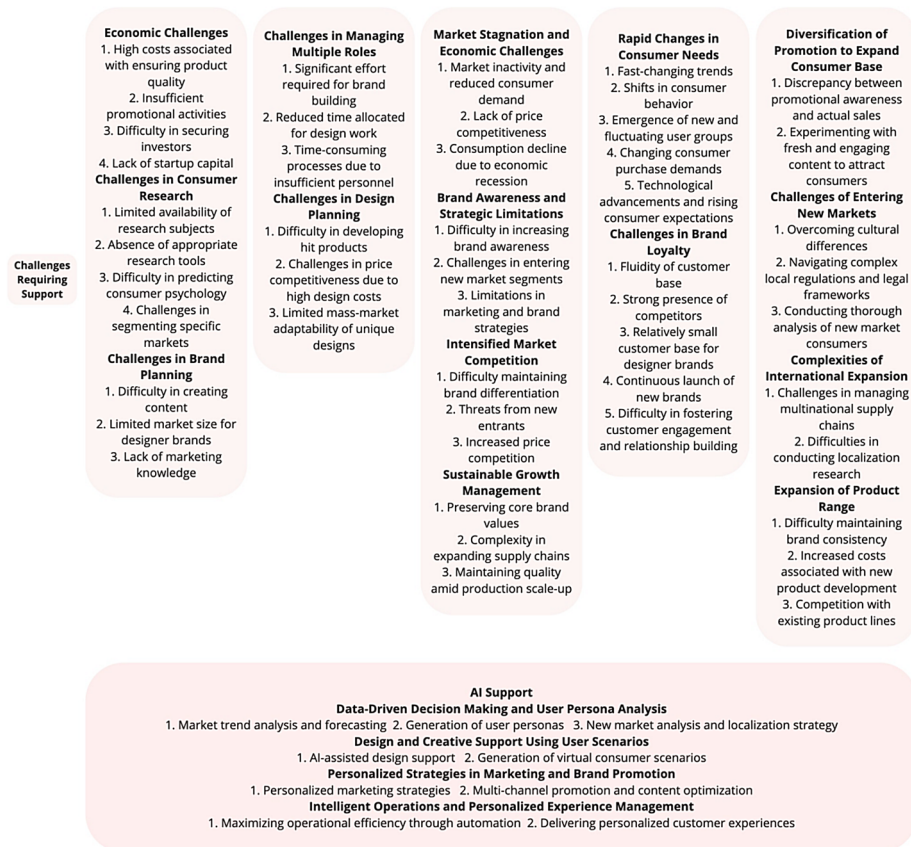


Fig. 7 Challenges in startup fashion brand development and the role of ai support in strategic solutions

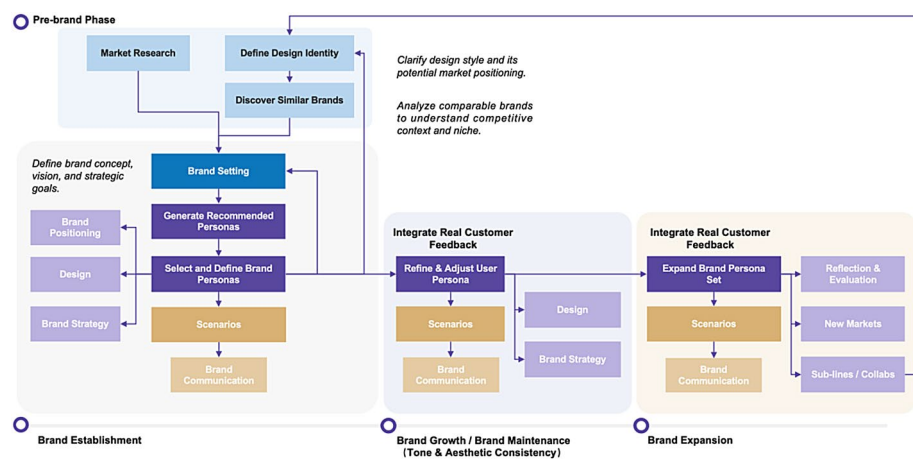


Fig. 8 P/S-driven branding process for fashion startups

Brand establishment phase: user persona and scenario development

Following self-assessment and market analysis, designers articulate their brand concept, vision, and objectives. Based on these inputs, the platform recommends potential user personas that align with the brand's positioning. Designers then refine and

select target personas to represent their core audience. These personas function as strategic user proxies that inform subsequent processes including brand positioning, design direction, and strategic planning. Scenario development follows, wherein contextual user-brand interactions are simulated to guide designers in communication strategy planning—capturing user motivations, usage environments, and purchase behaviors.

Growth and maintenance phase: iterative refinement

As the brand evolves, real user feedback is continuously integrated to adjust and refine previously defined personas and scenarios. This ensures coherence in brand tone and aesthetic direction while accommodating shifts in consumer behavior. The iterative nature of the platform allows for dynamic adaptation, reinforcing long-term brand consistency and user engagement.

Expansion phase: diversification and strategic scaling

At the expansion stage, designers leverage accumulated user data and real-time market responsiveness to extend the persona set and scenario diversity. This enables adaptation to a broader audience while supporting strategic diversification. Through persona-driven scenario modeling, designers can realign brand strategies, explore new market segments, and develop tailored communication approaches that foster scalable brand growth.

This structured, persona-oriented branding workflow equips fashion startups with a strategic framework to navigate branding complexities. By integrating consumer insights across each stage—positioning, strategy, design, and communication—it promotes coherent, data-driven, and scalable brand development.

Module construction and data requirements

To implement the AI-driven P/S Branding Platform proposed in this study, three core AI modules were developed to align with the specific stages of fashion designer brand development: (1) Style Analysis Module, (2) Text Processing Module, and (3) DeepSeek

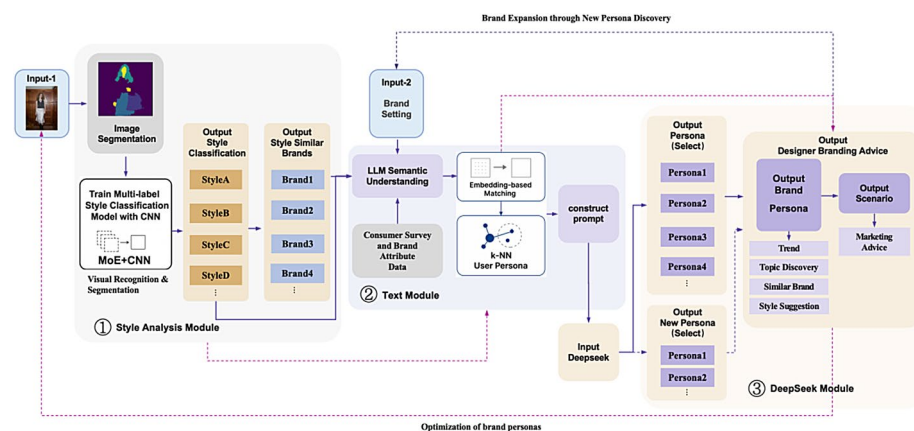


Fig. 9 System architecture of the AI-driven P/S branding platform

Module. As shown in Fig. 9, these modules collectively power the platform's persona/scenario-based branding approach.

Style analysis module

This module assists designers in identifying and contextualizing their stylistic inclinations through automated image-based analysis. Designers begin by uploading representative fashion images that reflect their design identity. Leveraging a multi-label CNN augmented with a MoE architecture, the system classifies each image into multiple aesthetic categories (e.g., minimal, romantic, sporty) and recommends visually similar designer brands for benchmarking purposes.

To improve classification accuracy, the module includes a preprocessing step that segments garments from backgrounds and human figures. The model was trained on a carefully curated dataset of designer brand images. Approximately 20% of the dataset was manually annotated by five fashion experts using an AI-assisted entity linking process, which mapped fashion items to established aesthetic taxonomies and trend descriptors. This semi-supervised training approach enhances the system's ability to recognize hybrid styles commonly found in contemporary designer fashion.

Text processing module

The second module is designed to interpret the designer's conceptual input and infer appropriate user persona suggestions. It fulfills two primary functions: (1) situating the brand concept within the broader market context and (2) matching brand-setting inputs—such as design vision, philosophy, and aesthetic focus—with relevant persona candidates.

Semantic embeddings of the designer's textual input are computed and compared against a curated persona database using a KNN algorithm. The database comprises both quantitative and qualitative data sources, including survey responses from 322 fashion consumers aged 20–30 in China and South Korea, and behavioral data mined from Instagram and Xiaohongshu. Each persona entry is structured around lifestyle values, aesthetic preferences, functional needs, and emotional motivations. This module bridges the gap between internal brand identity and external user targeting.

DeepSeek module

The final stage of the proposed AI-driven P/S Branding Platform is the DeepSeek module, designed to translate persona and scenario structures into actionable brand strategies. This module comprises five core functions, each supporting strategic decision-making in the later phases of brand development. These functions are powered by DeepSeek-VL, a vision–language model that combines designer prompts with domain-specific knowledge to generate scenario-based strategic insights.

First, based on prompts generated in the previous module, the system produces a set of candidate user personas through a pre-trained multimodal model. These initial outputs are presented for designer selection, refinement, or expansion to ensure alignment with specific branding goals. Second, the selected personas are enriched with detailed behavioral and psychological attributes, forming structured user profiles that guide downstream branding decisions. Third, the platform generates brand-building insights

derived from these profiles, including trend forecasts, style positioning directions, topic clusters, and comparable brand references. These outputs assist designers in aligning their product strategies with evolving consumer expectations and market trajectories. Fourth, scenario generation simulates user–brand interactions across various touch-points and lifestyle contexts, enabling designers to visualize real-world engagement. Fifth, the system synthesizes these scenarios into targeted marketing strategies, offering emotional triggers, content themes, and channel recommendations to support cohesive and resonant brand messaging.

Importantly, the DeepSeek module enables iterative persona evolution. Designers are encouraged to reflect upon, revise, and reconfigure their personas over time, supporting the exploration of emerging submarkets and the assessment of long-term brand growth trajectories. As such, this module acts as a strategic intelligence layer, shifting the role of AI from analytical support to participatory co-creation in branding.

These three modules form the technical foundation of the AI-driven P/S Branding Platform. In the following section, we present how these modules are operationalized within a user interface to support end-to-end branding decision workflows.

Platform implementation: AI driven–P/S branding prototype

System architecture overview

To transform the AI driven–P/S framework into a functional tool for fashion startups, a web-based platform prototype was developed. This implementation integrates the three core AI modules introduced in the previous section within an interactive user interface, enabling seamless branding workflow from aesthetic input to strategic output. The prototype was designed to support intuitive, modular use with minimal technical burden, allowing designers to engage with AI in a creative and decision-oriented manner.

The platform architecture consists of three functional layers: (1) the user interaction interface, (2) the AI-driven branding engine, and (3) the data and knowledge management layer. The interface was implemented using Streamlit and Python, enabling real-time interaction and modular task execution. The AI layer sequentially connects CNN-MoE based image classification, KNN-based persona matching, and DeepSeek-VL for scenario simulation and strategy generation. Data is stored and managed using JSON-based templates and local databases for rapid prototyping.

User interface and interaction design

The user interface of the platform is designed to reflect the cognitive and strategic workflow of branding development, particularly tailored for fashion startups. Drawing from principles of progressive disclosure and user-centered co-creation, the interface guides users through a modular sequence of interaction stages—each aligned with a critical branding decision.

The platform opens with a visually oriented start screen featuring a clearly designated “Start” button (as shown in Fig. 10). Once activated, the interface transitions into the first operational stage, prompting designers to upload representative product images that initiate the aesthetic analysis process (Fig. 11). The process begins with aesthetic anchoring, wherein designers upload representative product images that are analyzed using a multi-label CNN-MoE architecture. The platform classifies the visual input into

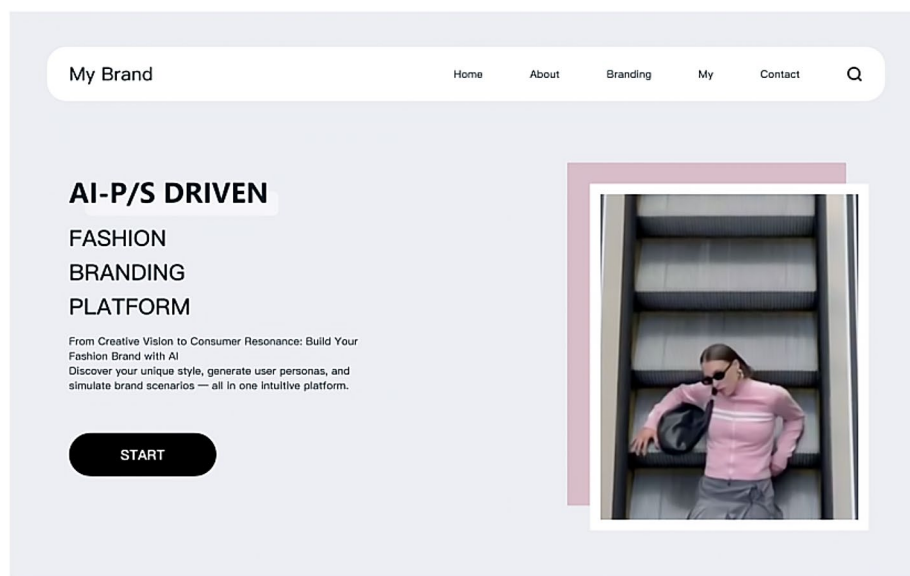


Fig. 10 User-centered interface for AI-powered branding workflow entry

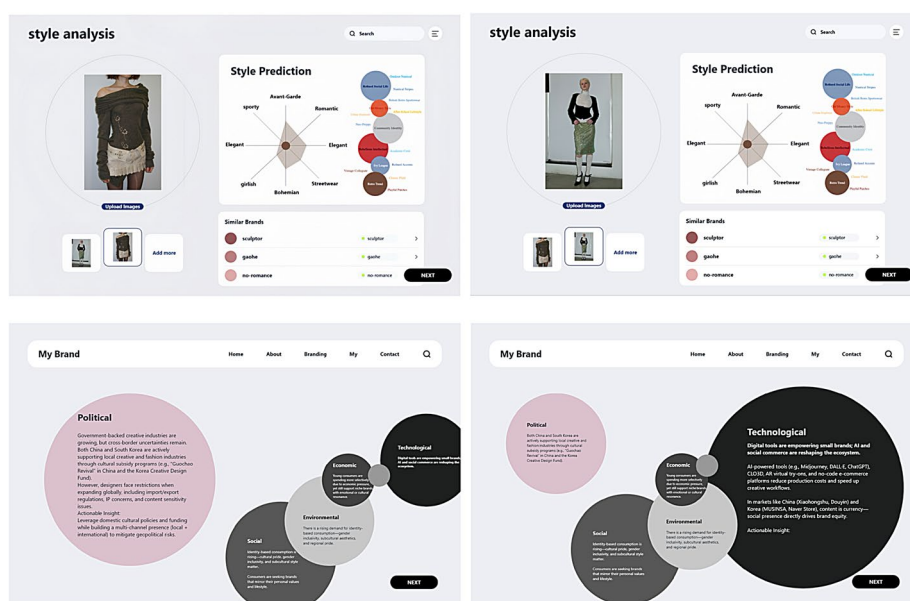


Fig. 11 Interface prototypes for style analysis and environmental scanning modules

multiple style categories and presents results through radar charts and brand similarity maps. These visualizations help designers objectively reflect on their aesthetic identity and explore comparative positioning within the design ecosystem.

(The upper panels show the style analysis interface, which identifies visual style clusters and recommends similar brands based on uploaded images using multi-label prediction. The lower panels depict the PESTE analysis module, presenting political, economic, social, technological, and environmental factors in an interactive visualization to guide strategic brand positioning.)

Prior to initiating the brand definition stage, the platform presents an overview of PESTE analysis results tailored to the fashion industry. This step allows designers to review macro-environmental factors—Political, Economic, Social, Technological, and Environmental—that may influence their strategic positioning (as shown in Fig. 12). Combined with insights derived from the previous aesthetic analysis stage, this contextual layer serves as a foundation for informed decision-making. Building upon these insights, designers proceed to articulate their brand identity through a structured input interface. This includes fields for defining the brand mission, core values, design philosophy, and market aspirations (as shown in Fig. 13). The objective is to translate intuitive design identities into clear, communicable brand concepts grounded in macro-environmental awareness.

To accommodate cross-regional differences in consumer behavior and competitive landscapes, the interface additionally requires designers to specify the target market location (e.g., South Korea, the United States, China). Incorporating this parameter ensures that subsequent analyses—particularly market diagnostics, persona interpretation, and scenario simulation—are contextualized according to the cultural, economic, and retail characteristics of the designated market. By anchoring the branding process in a clearly defined market environment, the system enhances the accuracy, relevance, and interpretability of its AI-driven recommendations.

In the next stage, the system integrates aesthetic features with brand inputs to generate a set of candidate personas. These personas—drawn from a behavioral dataset encompassing survey and social media data—capture archetypal consumer profiles such as “aesthetic-driven minimalists” or “eco-conscious trend seekers.” Designers can select, revise, or combine these candidates based on alignment with their brand vision (as shown in Fig. 13).

My Brand Home About Branding My Contact

BRAND SETTING

START YOUR BRAND JOURNEY

SECOND-CHANCER

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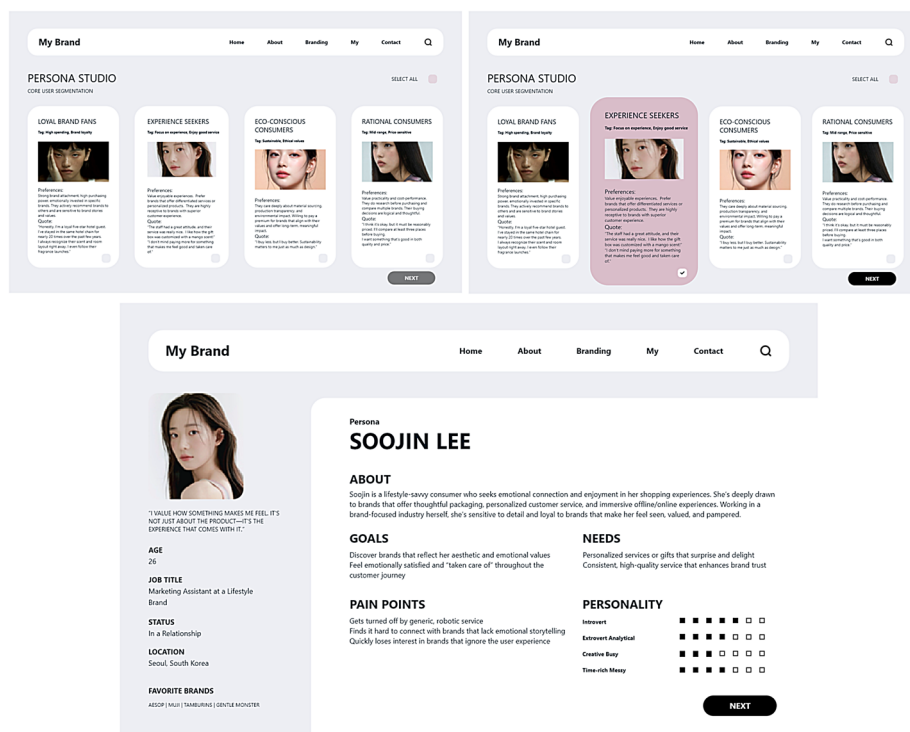


Fig. 13 Persona studio interface for target consumer profiling

After persona selection, the platform synthesizes a complete user persona profile, including demographics, values, lifestyle behaviors, and emotional motivators (as shown in Fig. 13). This structured persona acts as a pivot for downstream strategy generation, providing a psychologically and culturally grounded lens through which branding decisions can be made. With the finalized persona as input, the system generates market positioning insights, such as competitor benchmarks, trend trajectories, and semantic brand keywords (as shown in Fig. 14). These outputs are derived using an embedding model trained on a multi-source fashion corpus and help designers clarify their positioning, refine differentiation strategies, and inform their design direction.

Following this, the platform initiates the scenario simulation phase, generating narrative sequences that depict imagined interactions between the user and the brand. In this phase, the system automatically produces multiple online and offline interaction pathways—ranging from website browsing and social media encounters to in-store fitting and pop-up store experiences—allowing designers to understand how users might engage with the brand across diverse touchpoints. The generation of scenarios is guided by a structured inferential logic. The system first extracts core attributes embedded in the persona profile—such as lifestyle patterns, aesthetic orientations, consumption motivations, and body-related needs—and integrates these with brand-specific variables including positioning, visual tone, and intended value propositions. These inputs are then evaluated alongside contextual market conditions. Based on a weighted reasoning mechanism that considers motivational strength, affective tendencies, and behavioral preferences, the algorithm simulates three to five differentiated interaction pathways, each representing a plausible narrative trajectory within the user–brand relationship. In addition to system-generated scenarios, the

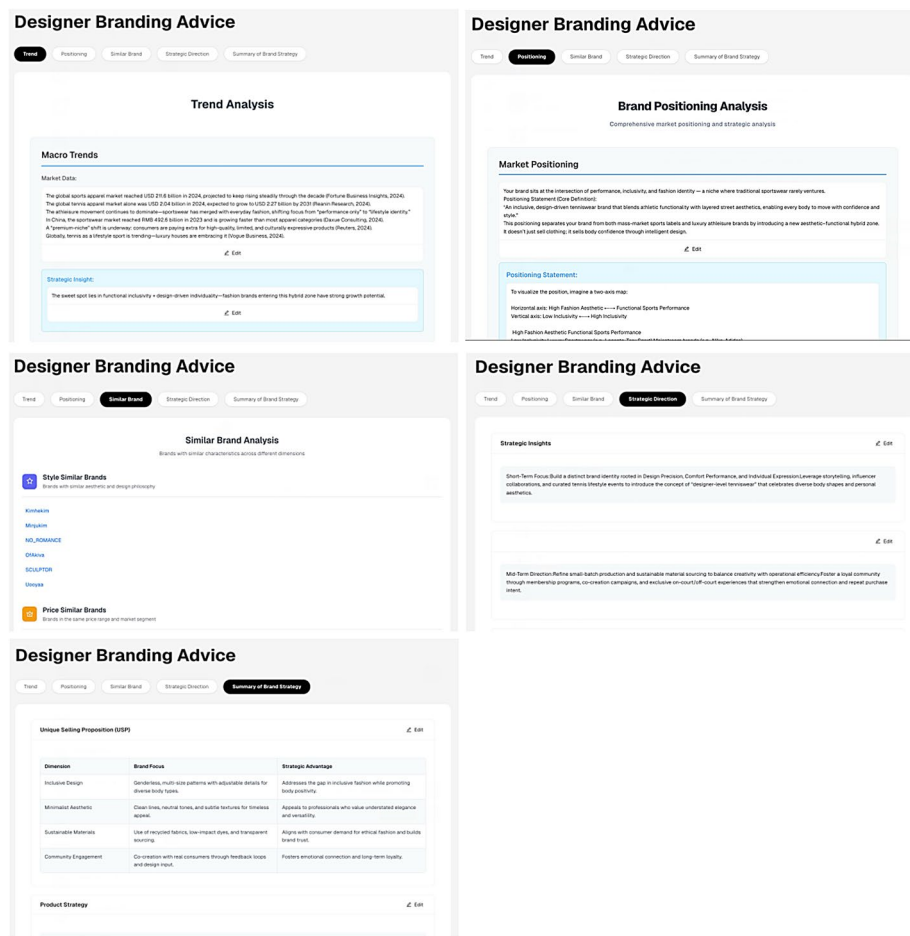


Fig. 14 Output interface of branding strategy

platform provides a scenario-extension function that allows designers to manually add or modify scenario nodes in accordance with specific branding goals, market circumstances, or research needs. The combination of automated generation and designer-driven augmentation enhances the realism, flexibility, and contextual fidelity of the scenario simulations.

Each scenario unfolds across five experiential stages—awareness, exploration, product experience, emotional response, and resolution—a structure informed by customer journey mapping and scenario-based interaction design (Carroll, 2003; Lemon & Verhoef, 2016) (as shown in Fig. 15). These simulations allow designers to visualize potential user engagement across both digital and physical touchpoints, supporting empathy-driven decisions in UX, storytelling, and campaign development.

In the final step, the platform produces AI-generated suggestions that align with the constructed persona and scenario, offering directional guidance for brand storytelling and user engagement (Fig. 15).

Discussion

To assess the perceived usability and functional value of the proposed AI-driven P/S Branding Platform, a scenario-based simulation test was conducted using structured templates rather than a fully implemented system. Through guided walkthroughs and

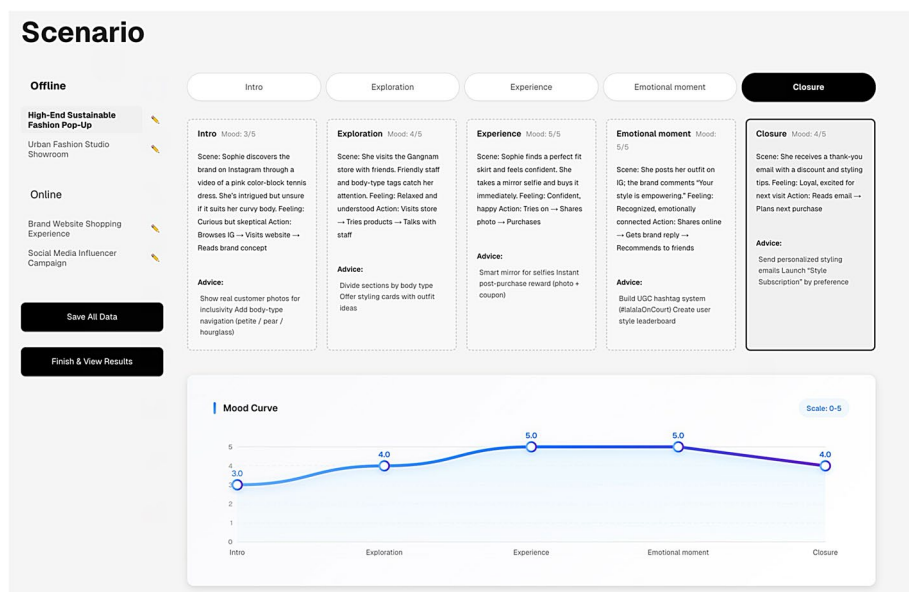


Fig. 15 Scenario-based marketing suggestions

interface mockups, six core modules of the platform—each corresponding to a key step in the branding process—were virtually demonstrated to participants. Five participants with backgrounds in fashion design were invited to complete a structured evaluation questionnaire based on their experience interacting with the platform prototype.

The questionnaire was constructed using an extended version of the Technology Acceptance Model (TAM). For each module, six dimensions were evaluated: (1) (PU) Result Demonstrability, (2) (PU) Job Relevance, (3) (PU) Output Quality, (4) (PEOU) Perceived Enjoyment, (5) (PEOU) Computer Self-Efficacy, and (6) BI. A five-point Likert scale was used (1 = strongly disagree; 5 = strongly agree).

Quantitative results indicated a generally high level of user acceptance. Among the PU subcomponents, result demonstrability and job relevance were rated highly, at 4.66 and 4.60 respectively, indicating strong alignment between the system outputs and practical branding needs. However, output quality received a comparatively lower score of 4.31, reflecting a degree of skepticism regarding the precision or depth of AI-generated content. In contrast, the PEOU dimensions received the highest scores, with perceived enjoyment and computer self-efficacy rated at 4.66 and 4.74, respectively. These results reflect strong user engagement and confidence in navigating the system. The overall behavioral intention to use the platform scored 4.69, reinforcing the perceived value of the system. At the construct level, the average scores were 4.52 for PU, 4.70 for PEOU, and 4.69 for BI, indicating that perceived ease of use may have a slightly greater influence than perceived usefulness in shaping users' intentions to adopt the platform (as shown in Fig. 16).

Participants also evaluated the platform's seven branding workflow stages, which were style recognition and market analysis based on uploaded images, brand setting based on analytical feedback, persona recommendation, persona generation, market

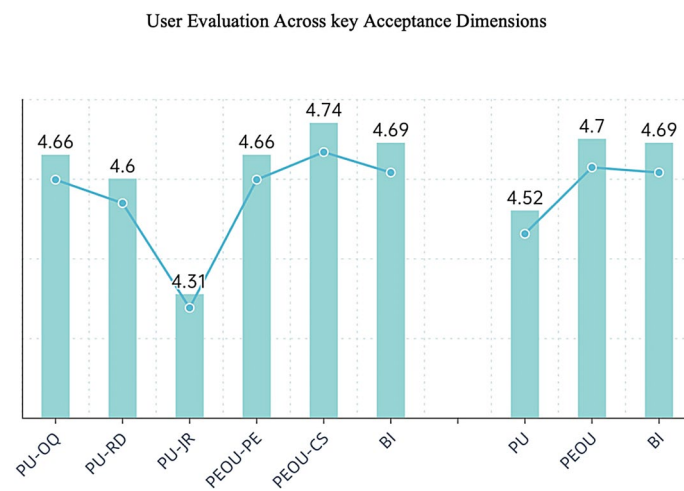


Fig. 16 User evaluation scores across TAM-based acceptance dimensions

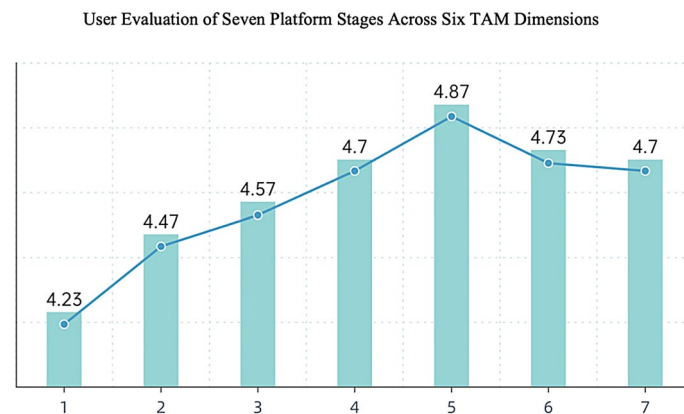


Fig. 17 User evaluation of seven platform stages across Six TAM dimensions

positioning and strategic keyword discovery, scenario generation, and marketing suggestion output. The data revealed a progressive increase in user satisfaction across these stages. Style recognition, the first stage, received the lowest score at 4.23, suggesting the need for improved interpretability of the system's visual analysis outputs. In contrast, the later stages received higher evaluations, with market positioning and strategic keyword discovery achieving the highest score of 4.87. Scenario generation and marketing suggestion output also received strong ratings of 4.73 and 4.70, respectively (as shown in Fig. 17). These findings indicate that participants perceived the strategic output functions of the system to be particularly useful and relevant.

While quantitative scores confirmed high levels of satisfaction across all modules, follow-up interviews offered deeper insights into perceived strengths and areas for improvement. Among the most appreciated features were the platform's modular clarity and visualized process flow, especially in style analysis, persona generation, and scenario-based recommendations. Designers reported that these tools effectively supported tasks that were traditionally time-consuming or lacked methodological structure.

One recurring concern was the uncertainty regarding the accuracy of AI-generated content, particularly with respect to market trend suggestions. Several designers acknowledged that they lacked a clear understanding of current fashion trends themselves, making it difficult to judge the validity of AI-generated insights. As one participant commented,

"I don't even know what the trend is right now, so I can't say whether what the AI gave me is useful or not."

Another frequently mentioned improvement was the need for fashion-specific variables in the persona module. Designers noted that in fashion, demographic or psychographic traits alone may be insufficient. Attributes such as body shape, fit preferences, and material sensitivities could offer more practical guidance for design decisions. Participants agreed that the inclusion of such attributes would enhance the platform's utility in product development.

Attitudes toward the P/S method varied based on prior exposure. Designers already familiar with the method showed great enthusiasm, describing the system as "exciting" and "potentially transformative" for brand building. In contrast, those new to the method initially expressed confusion, noting its deviation from traditional branding workflows. However, once they understood the system's logic and progression, all participants acknowledged its potential value for independent fashion brand development.

All participants unanimously identified the final modules—scenario generation and marketing strategy—as the most valuable features. These functions were particularly appreciated by those with limited experience in branding or business strategy. One designer noted,

"We can't be good at everything. I'm a designer first. I admit I'm not good at marketing, so this part is helpful."

Another added,

"Marketing in China is becoming too homogeneous and expensive. If this system can help me do scenario-based marketing tailored to my target audience and within a budget I can handle, it's extremely useful."

The persona functionality was also praised for streamlining research efforts. Designers noted that it could save considerable time otherwise spent on informal market research and provide an effective shortcut to better understanding their customers. Participants emphasized they did not want a system to decide for them, but rather a tool that aggregates and visualizes insights to support their creative autonomy. In this regard, the platform was seen as well-aligned with designer expectations.

Finally, the visual interface of the platform was widely appreciated. Designers noted that while current AI tools (e.g., ChatGPT, Midjourney) offer powerful capabilities, they are often presented in a text-heavy conversational format, requiring precise prompting and producing verbose outputs that feel disconnected from actual design workflows. By contrast, the prototype presented in this study was seen as more intuitive, user-friendly, and better suited for creative professionals. Several participants

expressed a strong desire for more professionally curated, domain-specific AI tools in fashion, calling them both “urgently needed” and “currently lacking.”

In summary, the evaluation demonstrated the conceptual feasibility of the AI-driven platform. Participants expressed strong interest in using the system in real-world branding processes, particularly for persona refinement and market communication planning. These findings support the value of integrating AI and the P/S method into designed brand strategies and provide a foundation for future platform development and refinement.

Conclusions

This study proposes and validates an AI-driven branding support system based on the P/S methodology, designed to provide structured, user-oriented strategic decision-making support for emerging fashion designer brands. This section discusses the theoretical and practical implications of the framework by focusing on the value of the P/S approach, the augmentation enabled by AI, and its adaptability to real-world market contexts.

At the theoretical level, this study advances the discourse on startup fashion branding by demonstrating the strategic value of integrating the P/S methodology into branding processes. The P/S approach enables designers to systematically interpret users’ lifestyles, aesthetic orientations, and value systems, thereby shifting brand conception from intuition-driven ideation toward a more evidence-based and user-informed strategic logic.

The incorporation of artificial intelligence, particularly models such as MoE-CNN and KNN, further enhances the operability and scalability of the P/S framework. Through multi-module collaboration across tasks including image-based style recognition, multi-label semantic embedding and style similarity retrieval, the platform enriches the semantic depth and market relevance of persona generation and scenario simulation. Artificial intelligence in this system functions not as a passive analytical tool but as a form of collaborative intelligence that bridges creative intuition with strategic execution. This enables designers to make more logical, data-informed and user-aligned branding decisions, particularly within resource-constrained and rapidly evolving fashion market environments.

From a practical level, the proposed platform addresses a critical gap in current fashion AI ecosystems, which largely emphasize operational tasks while lacking integrated, strategy-oriented support for brand development. By embedding branding logic at its core, the platform enables flexible application across multiple stages of brand evolution and demonstrates strong domain relevance in multi-label style classification, semantic modeling, and the implementation of the P/S methodology. Its regional adaptability—validated through localized user data and culturally responsive inference logic—further supports its contextual alignment in both Chinese and Korean markets.

Despite these strengths, limitations persist in AI transparency. Although designers responded positively to the system’s outputs, the lack of visualized reasoning pathways and data references constrained interpretability and undermined user trust. Future development should prioritize explainability by incorporating visual logic flows, data traceability, and decision rationale indicators. Benchmarking against alternative AI systems is

also necessary to evaluate comparative performance in terms of accuracy, scalability, and transparency.

As this study primarily focused on early-stage branding, further validation is needed to assess the platform's adaptability across subsequent lifecycle phases, including growth, maintenance, and expansion. To ensure global scalability, future research should incorporate more heterogeneous datasets and enhance algorithmic sensitivity to cultural variation. Additionally, to increase design-level applicability, future iterations should integrate embodied parameters—such as body shape, dressing behavior, and material preferences—and establish system-level linkages with tools like CLO 3D and textile-material databases. These advancements will reinforce the platform's potential as a scalable, adaptive, and culturally attuned branding infrastructure within an increasingly complex fashion ecosystem.

Abbreviations

P/S	Persona/scenario
MoE-CNN	Mixture-of-experts convolutional neural network
LLM	Large language model
KNN	K-nearest neighbors
GAN	Generative adversarial network
NLP	Natural language processing
UCD	User-centered design
TAM	Technology acceptance model
PU	Perceived usefulness
PEOU	Perceived ease of use
BI	Behavioral intention

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Author contributions

NM and JHL conceived the ideas experimental design, NM collected the data and performed the experiments, interpreted the results, and drafted the analysis manuscript. JHL supervised and gave continuous support to the study structure, performed the experiment successfully, and revised the manuscript. All authors read and approved the final manuscript.

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The datasets generated and analyzed during the current study are available from the corresponding author on reasonable request.

Declarations

Ethics and consent

This research was conducted under the approval and supervision of Yonsei University Institutional Review Board (IRB Approval No: 7001988–202507-HR-2797–02) regarding ethical issues including consent to participate.

Ethical issues including consent to participate

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Competing of interests

The authors have no conflicts of interest regarding this research, authorship, and/or publication of this article.

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