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Temporal Dynamics of Academic Research and Public Attention toward Generative AI in Fashion Design: A Bibliometric and Baidu Index Study

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Abstract

Generative AI has moved quickly into fashion design since 2022, yet how this diffusion plays out across academic and public spheres has received little empirical attention. We analyzed 855 Web of Science publications (2014 to 2025) alongside Baidu Index search data from the Chinese market. The bibliometric record falls into three phases: algorithmic exploration, application development, and scenario empowerment. A qualitative comparison of the two time series shows that the lag between growth in public search interest and growth in academic output appears to have narrowed from roughly 18 to 24 months before 2020 to about 6 to 12 months after 2022, suggesting that the two domains are becoming more closely coupled. Formal causal testing is needed to confirm the direction of influence.

Keywords: Fashion design; AI-generated content; Design innovation; Technology diffusion; Human-AI collaboration

1 Introduction

In technology-intensive manufacturing, the diffusion path from academic research to industry adoption is well mapped and typically follows a measurable lag. In design-driven creative fields, the process may work differently because aesthetic judgment, cultural sensitivity, and craft traditions matter alongside technical performance, yet the question has received little empirical study. The current wave of generative AI in fashion design offers a timely case. In the BoF-McKinsey State of Fashion 2024 survey, 73 percent of executives called it a top business priority, and public platforms are filled with AI-generated garments, trend forecasts, and pattern explorations. Academic research, meanwhile, has focused on model architectures, training regimes, and image fidelity [1, 2]. Both sides agree that AI can assist designers but disagree about where the technology reaches its limits and how labor should be divided between humans and machines [3, 4]. Whether academic output and public interest move in lockstep, whether one leads the other, and whether that relationship is changing are open empirical questions.

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The research based on human-AI design collaboration is thin. Applications keep expanding, covering trend forecasting [7], personalization [8], and sustainable production planning [9], and a rough consensus has formed that color matching and pattern generation suit AI while fabric hand-feel and cultural symbolism call for human judgment [5, 6]. But these task-level observations tell us nothing about how the broader landscape of research and public interest has evolved or whether the two move in tandem. Existing reviews cover only part of the picture: a narrow application [10], a single tool [11], or one technical pathway. None has examined the temporal relationship between scholarly output and public attention. The stakeholder perspective in technology adoption research [12] reminds us that brands, consumers, media, supply chain partners, and regulators all shape how a technology is adopted [13]. A full stakeholder analysis goes beyond the scope of the present study. Still, the multi-actor landscape motivates our choice to examine both formal academic output and informal public search behavior as complementary windows on diffusion.

This study addresses three research questions. What are the publication trends in generative AI fashion design research from 2014 to 2025? What temporal and geographic patterns appear in Chinese public search interest in AI design tools? And are there observable temporal associations between public attention and academic output? Earlier diffusion research has typically relied on a single indicator, either publication counts or market adoption data, to characterize diffusion curves. Pairing the two lets us ask whether the lag structure between academic and public attention is stable or shifting, and what the answer might imply for how creative industries absorb new technologies.

2 Methods

2.1 Data Source and Sample

Answering these questions requires a record of what the research community is producing and what the broader public is paying attention to. We combined three methods. Baidu Index analysis picks up public attention signals. Bibliometric analysis maps the structure and trajectory of academic knowledge production. A GM(1, 1) grey prediction model projects trends forward from historical data as an exploratory exercise. Baidu Index patterns provide context for interpreting bibliometric findings, and the bibliometric timeline serves as a baseline against which shifts in public attention can be gauged.

We measured public attention with the Baidu Index. China had 1.123 billion internet users as of June 2025 (penetration rate 79.7 percent)[14], and Baidu holds a leading position in mobile search. Regarding survey methods, the Baidu Index offers larger sample sizes, real-time availability, and reduced respondent bias [15]. Keywords were organized into two tiers. At the concept level, AI captures foundational technology interest (steady volume since 2014), and AI Painting captures the image-generation domain (which surged after late 2021). At the tool level, we included Midjourney (a leading international commercial platform), Stable Diffusion (a leading open-source model), and Wenxin Yige (a leading domestic Chinese tool). Concept-level keywords support long-run analysis across the full 2014 to 2025 window; tool-level keywords allow a focused look at the post-2022 adoption surge. A limitation of this component needs to be stated up front. These keywords capture general interest in AI image generation; they cannot isolate searches specific to fashion design. We tried fashion-focused terms (“AI 服装设计”, “AI 时装”), but the volumes were too low for trend analysis. That gap is itself telling. It suggests that public engagement with AI in fashion currently runs through general-purpose image tools rather than fashion-specific channels, which fits the early-diffusion picture the bibliometric data paint. Throughout this paper, the Baidu Index results should be interpreted as a measure of general interest in AI image generation. This category includes fashion but is not limited to it. The cross-method comparisons presented later should be understood with this difference in scope in mind.

For the academic record, we searched the Web of Science Core Collection (SCI-Expanded, SSCI, A&HCI). Boolean queries cross-matched generative-AI terminology with fashion and apparel design terms, spanning January 2014 through December 2025. The initial search returned 960 records. After excluding editorials, book reviews, conference notices, and papers focused exclusively on e-commerce recommendation or textile manufacturing rather than design, 855 records remained (Figure 1). We ran the bibliometric analysis in R with the Bibliometrix package, following standard workflows. Keyword co-occurrence used a minimum frequency of 5. Thematic evolution was mapped across three slices: 2014 to 2019, 2020 to 2022, and 2023 to 2025.

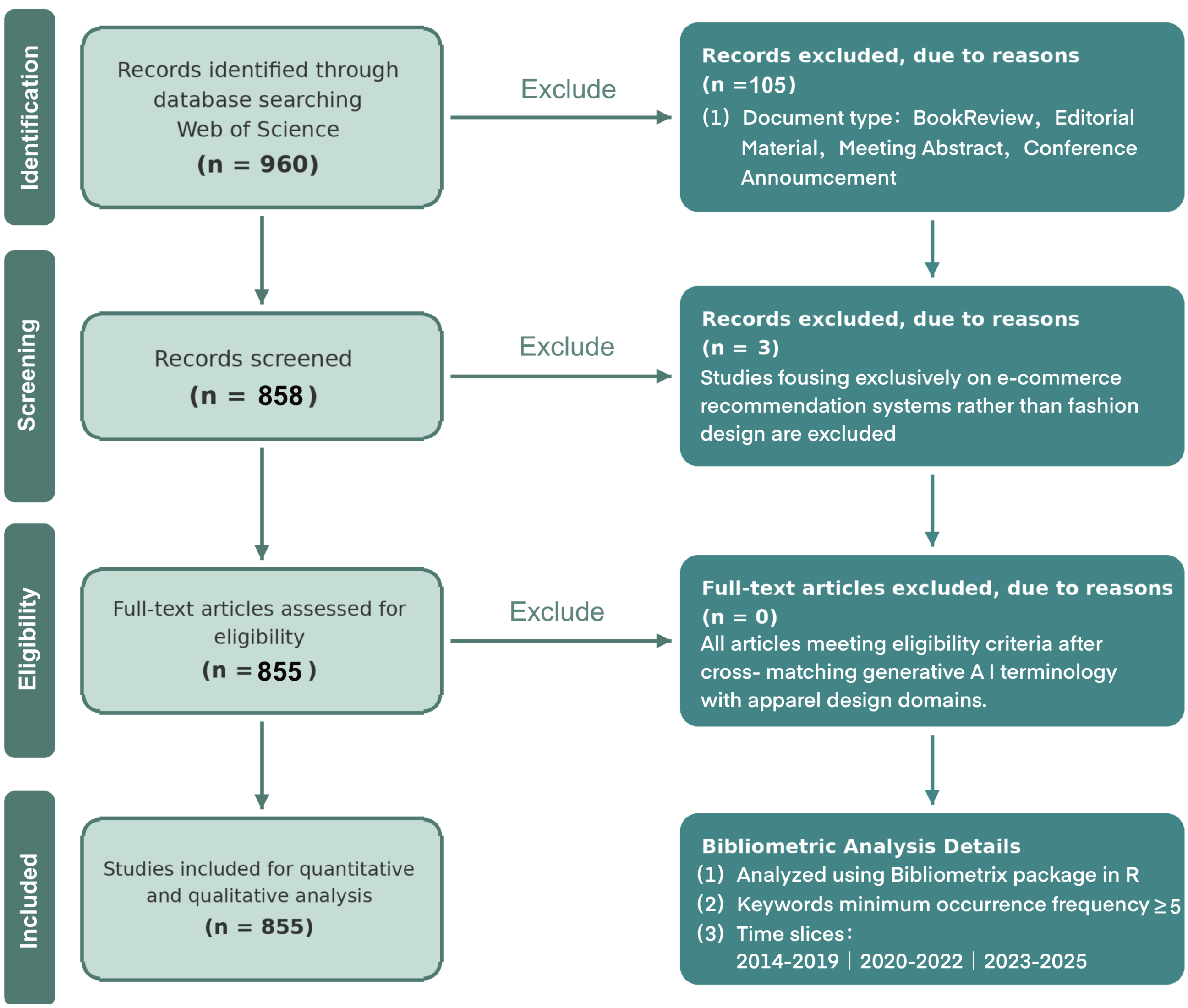

Fig. 1: PRISMA Flow Diagram of Literature Screening Process

2.2 Grey Prediction Model

As an exploratory exercise, we applied the GM(1, 1) grey prediction model. Introduced by Deng Julong in 1982 for settings with small sample sizes and incomplete data, the model derives a first-order ordinary differential equation from the accumulated generating operation (1-AGO) of the raw data sequence.

Given original sequence:

$$X^{(0)} = (x^{(0)}(1), x^{(0)}(2), \cdots, x^{(0)}(n)) \tag{1}$$

The 1-AGO produces:

$$X^{(1)} = (x^{(1)}(1), x^{(1)}(2), \cdots, x^{(1)}(n)) \tag{2}$$

where:

$$x^{(1)}(k) = \sum_{i=1}^{k} x^{(0)}(i), \quad k = 1, 2, \cdots, n \tag{3}$$

The mean sequence is defined as:

$$Z^{(1)} = (z^{(1)}(2), z^{(1)}(3), \cdots, z^{(1)}(n)) \tag{4}$$

where:

$$z^{(1)}(k) = \frac{1}{2}(x^{(1)}(k) + x^{(1)}(k-1)) \tag{5}$$

The GM(1, 1) model in its mean form is expressed as:

$$x^{(0)}(k) + az^{(1)}(k) = b, \quad k = 2, 3, \cdots, n \tag{6}$$

with development coefficient a and grey input b. The whitening equation:

$$\frac{dx^{(1)}}{dt} + ax^{(1)} = b \tag{7}$$

The parameters are estimated using the least squares method:

$$\hat{a} = (a, b)^T = (B^T B)^{-1} B^T Y \tag{8}$$

where:

$$Y = \begin{pmatrix} x^{(0)}(2) \\ x^{(0)}(3) \\ \vdots \\ x^{(0)}(n) \end{pmatrix}, \quad B = \begin{pmatrix} -z^{(1)}(2) & 1 \\ -z^{(1)}(3) & 1 \\ \vdots & \vdots \\ -z^{(1)}(n) & 1 \end{pmatrix} \tag{9}$$

The time response function of the whitening equation yields:

$$\hat{x}^{(1)}(k+1) = \left(x^{(0)}(1) - \frac{b}{a}\right) e^{-ak} + \frac{b}{a} \tag{10}$$

Predicted values follow from inverse AGO:

$$\hat{x}^{(0)}(k+1) = \hat{x}^{(1)}(k+1) - \hat{x}^{(1)}(k) \tag{11}$$

The model assumes roughly exponential growth, but the field hit a structural break with the diffusion-model advances of 2022. Because the training window (2016 to 2019) sits entirely before that break, the projections are best read as what-if extrapolations, not forecasts.

3 Results

3.1 Temporal and Spatial Patterns of Public Attention

All five keywords had enough Baidu Index volume for trend analysis. The patterns reported here are descriptive; no formal causal tests were run. Over the full study window (Figure 2), AI maintained a low, flat baseline from 2014 to 2019, with a gradual uptick beginning around March 2016, when AlphaGo's victory brought AI into mainstream conversation. AI Painting sat near zero until late 2021, then climbed quickly alongside the public releases of DALL-E 2, Midjourney, and Stable Diffusion in 2022. Tool-level keywords surged after those releases; Midjourney search volume grew roughly 50-fold between July and December 2022 (based on raw Baidu Index values). Across keywords, interest in the general concept appeared first, followed by the application domain, then individual tools, a sequence that fits standard diffusion models, in which awareness precedes adoption.

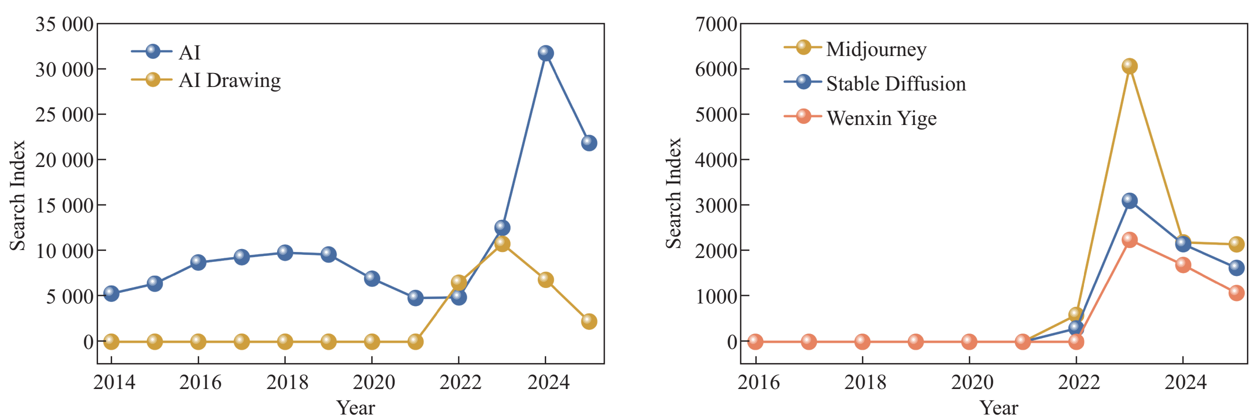

Fig. 2: Temporal Evolution of Baidu Search Indices for AI-Related Keywords from 2014 to 2025

Read together, the search data trace three stages: a germination phase (2014 to 2019) with consistently low indices; a growth phase (2020 to 2022) in which attention rose alongside diffusion-model advances; and an explosion from 2023 onward, with exponential growth and multiple peaks per year tied to tool updates and digital fashion events. Slight seasonal bumps in March through April and September through October line up with fashion week schedules, but we cannot confirm a causal link. Geographically (Figure 3), Beijing, Guangdong, Shanghai, Zhejiang, and Jiangsu form a high-attention core. A second tier (Sichuan, Shandong, Hubei, Henan, Fujian) follows at lower intensity. Attention tracks regional wealth and digitalization closely.

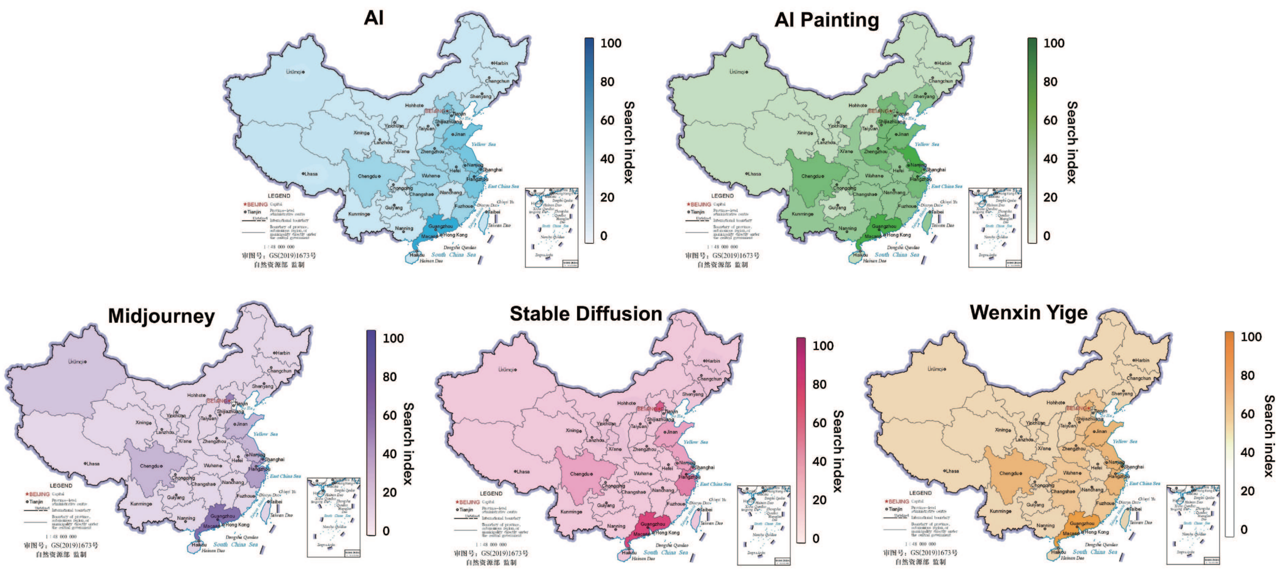

Fig. 3: Geographic Distribution of Search Intensity Across Chinese Provinces

3.2 Evolution of Academic Knowledge Production

Analysis of annual publication volume curves reveals that academic research has progressed through three developmental phases consistent with the maturation of underlying technologies, as shown in Figure 4. The period from 2014 to 2019 represented the technological germination phase, characterized by low publication volumes averaging fewer than 50 annually. Research was primarily driven by the computer science community, focusing on theoretical exploration of foun-

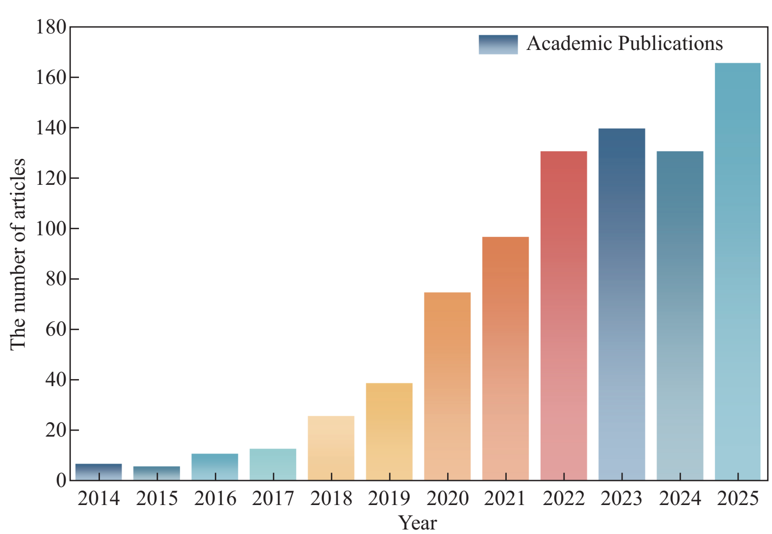

Fig. 4: Annual Publication Volume in Generative AI Fashion Design Research from 2014 to 2025

dational algorithms such as generative adversarial networks. Low publication volumes reflected insufficient image quality and controllability for design applications.

The period from 2020 to 2022 marked a turning point. Annual publication growth exceeded 40 percent, driven by rapid advances in diffusion models that shifted the technical frontier away from GANs. As the tools became more capable, research attention moved toward concrete applications: style generation, print pattern design, and fabric texture synthesis. This broadening of scope drew in researchers from design studies and textile engineering, fields that had been largely absent from the earlier phase. From 2023 to the present, the field has entered a phase of exponential growth in publication volume. Technical work deepened around human-AI collaborative workflows and multimodal interaction, while an entirely new set of concerns emerged around ethics, cultural heritage, and sustainable design. The field that had begun as a computer vision problem was now engaging with social and cultural dimensions that no purely technical framework could address.

The field has formed a clustered pattern centered on universities, research institutions, and technology enterprises, as shown in Figure 5. China, the United States, and the United Kingdom represent primary sources of knowledge production. Tsinghua University and The Hong Kong Polytechnic University have made notable contributions, often in the areas of cultural heritage and design applications. Foundational achievements have predominantly appeared in prominent venues, including CVPR, ICCV, and IEEE Transactions, as detailed in Table 1. The presence of IEEE Transactions on Medical Imaging in this list is worth noting. Architectures such as U-Net were originally developed for biomedical image segmentation. Yet they readily transferred to fashion tasks, including virtual try-on and garment generation, because accurate modeling of visual structure and spatial detail is equally central to both domains. That a medical imaging journal ranks among the top publication venues for fashion AI research illustrates how deep learning has crossed traditional disciplinary boundaries at the technical level.

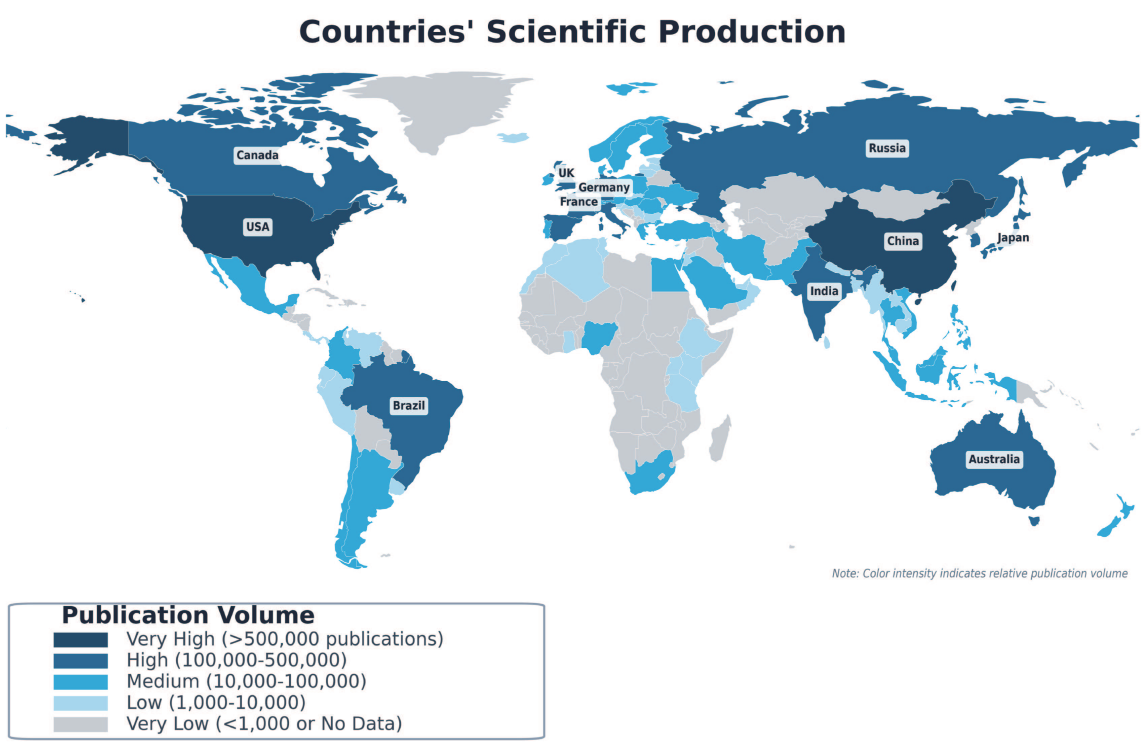

Fig. 5: Geographic Distribution of Academic Publications by Country

Table 1: Top 10 Publication Venues by Article Count

Rank	Source	N. of Documents
1	IEEE Access	30
2	Applied Sciences-Basel	16
3	International Journal of Clothing Science and Technology	15
4	Electronics	13
5	IEEE Transactions on Multimedia	13
6	Neurocomputing	13
7	Sensors	13
8	Expert Systems with Applications	11
9	IEEE Transactions on Medical Imaging	11
10	Scientific Reports	10

Through dynamic evolution analysis, as illustrated in Figure 6, a developmental pathway emerges from methodological exploration to technological application and subsequently to scenario empowerment. Style, color, and fabric constitute the three fundamental elements of fashion design, and generative AI achieved substantial progress across all three from 2020 to 2022. Tools such as Midjourney and Stable Diffusion became capable of generating high-quality images from textual descriptions. After 2023, research attention moved toward specific application contexts, with wearables and digital fashion emerging as particularly active sites of integration.

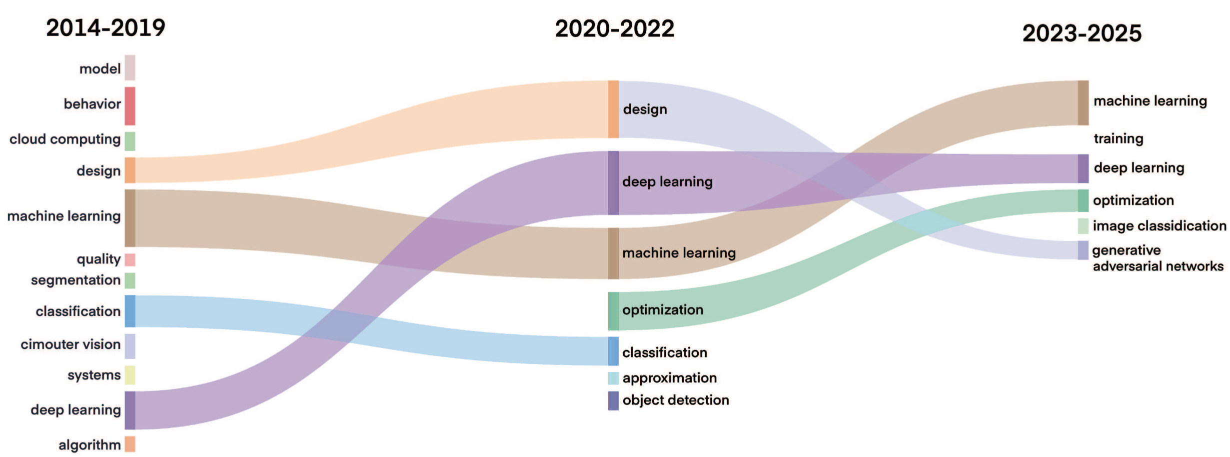

Fig. 6: Thematic Evolution Across Three Research Phases

Highly cited publication analysis, as presented in Table 2, reveals that foundational algorithm papers dominate the citation rankings, indicating that the field's knowledge base remains anchored in contributions from computer science. Virtual try-on has consolidated into a recognizable application cluster, but works addressing ethics, cultural heritage, or sustainability are conspicuously absent from the top-cited lists. Cross-institutional collaboration between computer science departments and fashion schools remains limited. The field may be interdisciplinary in subject matter, but its academic knowledge production is not.

Table 2: Top 15 Highly Cited Publications in Generative AI Fashion Design

Rank	Author	Year	Source	DOI	Citations
1	He KM	2016	PROC CVPR IEEE	10.1109/CVPR.2016.90	87
2	Liu ZW	2016	PROC CVPR IEEE	10.1109/CVPR.2016.124	56
3	Simonyan K	2015	ARXIV	10.48550/ARXIV1409.1556	53
4	Krizhevsky A	2012	ADV NEURAL INF PROCE	10.1145/3065386	47
5	Ronneberger O	2015	LECT NOTES COMPUT SC	10.1007/978-3-319-24574-4.28	46
6	Vaswani A	2017	ADV NEUR IN	ARXIV1706.03762	43
7	Goodfellow IJ	2014	ADV NEUR IN	ARXIV1406.2661	41
8	LeCun Y	1998	P IEEE	10.1109/5.726791	41
9	LeCun Y	2015	NATURE	10.1038/NATURE14539	38
10	Han XT	2018	PROC CVPRIEEE	10.1109/CVPR.2018.00787	36
11	HeuselM	2017	ADV NEUR IN	ARXIV1706.08500	32
12	Isola P	2017	PROC CVPRIEEE	10.1109/CVPR.2017.632	31
13	wang Z	2004	IEEE T IMAGE PROCESS	10.1109/TIP2003.819861	30
14	Zhang R	2018	PROC CVPRIEEE	10.1109/CVPR.2018.00068	29
15	ZHU JY	2017	PROC CVPRIEEE	10.1109/ICCV.2017.244	26

3.3 Trend Projection

Because the GM(1, 1) model was fitted to 2016–2019 data, well before the 2022 diffusion-model breakthrough, everything below should be read as a what-if scenario rather than a forecast. We chose that training window because the data satisfy the exponential-growth assumption, with all three indicators returning MAPE values below 2.2% and P values of 1.00, meeting the standard threshold for model adequacy. Under the model, the three dimensions diverge (Figure 7). Digital design shows the steepest climb, a projected 10.8-fold rise from 273 in 2016 to 2 958 in 2030. Sustainable design grows by about 3.9-fold (from 633 to 2 476). AI design tools, starting from a much higher base, grow a modest 1.3-fold (8 699 to 11 423). The projected digital-design trajectory plausibly reflects the ongoing shift from legacy design software to AI-assisted tools. Steady growth in the sustainability dimension tracks with the value of AI in cutting sample waste and optimizing material use. These are our interpretive reads on the model output, not conclusions derived from it.

3.4 Cross-Method Comparison

Placing the two time series side by side (Figure 8) reveals a shifting temporal relationship. The academic upturn that began in 2020 occurred about 24 months before the Baidu Index spike, with scholarly activity growing first. But the late-2022 explosion in search interest, linked to Midjourney V4 and ChatGPT, preceded the next jump in publication output in 2023, suggesting that the flow does not always run from academia to the public. The gap between the two

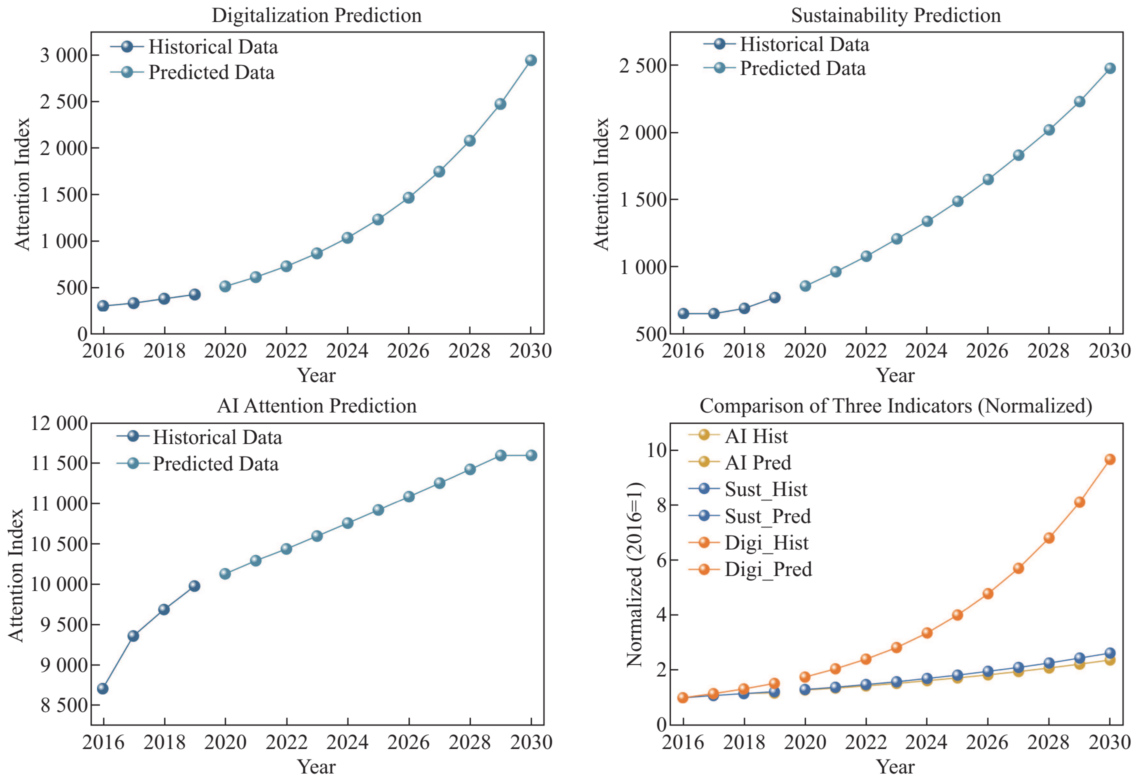

Fig. 7: GM(1, 1) Trend Projections for Three Dimensions from 2016 to 2030

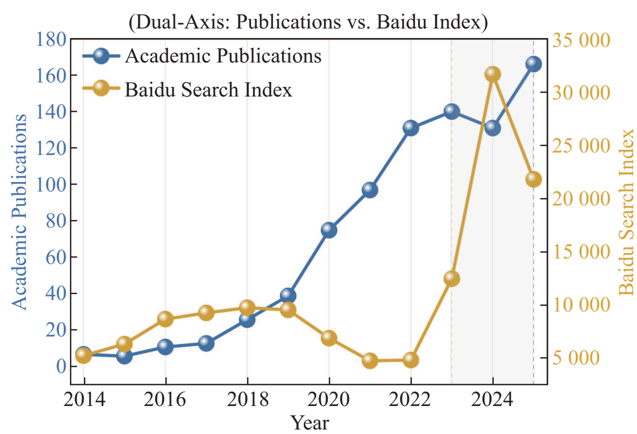

Fig. 8: Temporal Relationship Between Academic Publications and Public Search Interest

curves also appears to be closing, from roughly 18 to 24 months in the 2017 to 2020 window to roughly 6 to 12 months in 2022 to 2024. On the geographic side, the five highest-attention Baidu provinces overlap heavily with the regions hosting the most productive research institutions, reflecting the co-location of research capacity and digital adoption along China's developed coast. These patterns should be understood as descriptive. The Baidu Index covers only Chinese search behavior, while Web of Science publications are a global, largely English-language corpus, and the two measure different things. The apparent narrowing of the lag between them could reflect heavier media coverage, easier public access to tools like Midjourney, faster academic pivots toward commercially visible topics, or some combination of all three. Disentangling these factors will require time-series methods that go beyond what we have done here.

4 Discussion

The question motivating this study was whether the temporal relationship between academic knowledge production and public attention toward generative AI in fashion design shows a discernible and changing pattern. The bibliometric analysis of 855 publications and the Baidu Index data point to three findings worth discussing.

The three-phase trajectory visible in the bibliometric record broadly follows the technology S-curve observed in other innovation domains, though the logic of each phase is specific to fashion. Early work was driven largely by computer scientists whose primary concern was image fidelity rather than design relevance. As the technology matured, textile engineers and design scholars entered the conversation, directing attention toward style generation, print design, and fabric-texture synthesis. The current period has broadened the agenda to include ethics, cultural heritage, and sustainability [16]. Across these phases, the evolving technology appears to be reshaping the design value chain. Tools have gotten easier to use, lowering the barrier to concept creation while raising questions about originality and intellectual property. In most jurisdictions, a purely AI-generated work cannot be copyrighted; the treatment of AI-assisted works with meaningful human input is still legally unsettled. At the same time, generative AI remains weak on fine-grained control: three-dimensional draping, for instance, still requires physical prototypes. The geographic data add a further observation: attention concentrates where wealth, tech infrastructure, and fashion-industry density already cluster [17].

The most notable empirical finding is the apparent shortening of the temporal lag between academic and public attention, from roughly 18 to 24 months before 2020 to 6 to 12 months after 2022 (Section 3.4). We arrived at that estimate through qualitative visual comparison rather than time-series regression, so it should be treated as a hypothesis. The direction of the pattern does, however, line up with accelerating diffusion cycles reported in other technology areas. Tools like Midjourney require no programming skills, lowering the barrier to experimentation. Social media translates research developments into public conversation faster than older channels did. And researchers themselves appear to be responding more quickly to topics with commercial visibility. Confirming the shortening with formal methods would have practical relevance for how institutions and firms anticipate adoption timing.

The bibliometric data do not directly demonstrate that the designer's role is changing, but they are compatible with the idea. Human-AI collaboration emerged as a major keyword cluster in the 2023 to 2025 phase (Section 3.2), and external work points in the same direction. Jin et al. (2024) had 19 participants, a mix of students, professionals, and researchers, who used Midjourney and DALL-E for early-stage ideation and found that evaluation and refinement dominated the workflow [19]. On the industry side, Collina Strada's Spring 2024 collection is reportedly the first instance of a designer using AI to generate an entire runway lineup; creative director Hillary Taymour fed prior-season images into Midjourney and iterated over several weeks [18, 20]. Both examples suggest that the designer's core work may be moving from making to curating generative output. But small-N studies and single cases cannot settle the question, and larger-sample work is needed.

The thematic evolution analysis (Figure 6) also flags three application clusters that emerged between 2023 and 2025. Mass customization comes first: AI-driven on-demand design could reconfigure the space between fast fashion and bespoke production, but its realization depends on consistent design quality, IP resolution, small-batch economics, and consumer willingness to pay a premium [21]. Sustainable design optimization is the second cluster. AI can help with material simulation, pattern efficiency, and production planning [22]; brand-level cases have shown how AI tools integrate into the Double Diamond process to support sustainability goals [23], and AI-driven demand forecasting may reduce overproduction, though reported results vary across settings [24]. Cultural heritage preservation is the third. Researchers have applied generative models to Miao batik [25], Dunhuang murals [26], and Peking Opera masks [27], and diffusion models now handle pattern generation, digital reconstruction, and broader access to heritage resources [28]. The work has economic and social value but also carries risks: cultural appropriation, flattened symbolism, unequal benefit sharing, and the absence of source-community voices in governance. All three clusters share a structural constraint: cultural bias in training data. Published audits show that datasets skew toward particular aesthetic conventions, narrowing the range of what models can produce [29]. Broadening cultural representation at the data stage and drawing on heritage scholarship can improve diversity, but no threshold for adequate representation has been established [30]. Domain-adapted architectures show promise. A knowledge-graph system trained on Chinese dynastic clothing supports heritage queries [31], and deep-learning models trained on Indian textile imagery can classify crafts such as Ajrakh, Bandhani, and Kalamkari [32]. The open question is whether such systems go beyond surface pattern recognition to encode genuinely meaningful cultural distinctions.

The GM(1, 1) projections extrapolate pre-2022 growth trends forward. If those trends held, digital design attention would climb from 1, 847 in 2025 to 2, 958 by 2030, and sustainable design from 1, 894 to 2, 476. These are scenario figures under a specific assumption. Survey data indicate that most fashion executives view generative AI as a near-term priority. Still, outcomes depend on how fast the technology matures, what it costs, and whether organizations are prepared to reorganize around it.

There are several limitations to the study. The Baidu Index captures only online search behavior, missing offline discussions and social media conversations. The two data sources are not parallel. The Baidu Index tracks Chinese search behavior, while Web of Science covers globally indexed, mostly English-language scholarship and omits the fast-growing body of Chinese-language AI research [33]. We chose this combination deliberately. Chinese public attention offers a window into technology adoption in the world's largest internet market and one of its biggest fashion markets; the WoS literature maps globally indexed knowledge production [34]. We do not claim one-to-one correspondence. We looked for temporal patterns, lag durations, and growth trajectories that might illuminate diffusion dynamics beyond the Chinese context. The contrast between regional public reception and global academic output may itself be informative; other researchers studying technology diffusion have combined regional market signals with global publication data similarly [35]. Several directions follow from these limitations. First, by pulling in social media, e-commerce, and design-community data and running NLP on user-generated content, we would get a fuller picture of adoption. Second, the designer-role proposition needs testing through interviews, observation, and controlled design tasks, with attention to how skill level and organizational setting shape collaboration. Third, integrating non-Western aesthetics into AI training requires cross-national comparative work and culturally grounded evaluation. Fourth, tracing how AI reshapes fashion value chains requires industry surveys and econometric analysis that can separate short-run disruption from long-run structural change.

5 Conclusion

This study traced how academic output and public attention toward generative AI in fashion design have evolved from 2014 to 2025 and asked whether the two trajectories are temporally related. A bibliometric analysis of 855 publications, combined with Baidu Index search data, revealed a three-phase arc of algorithmic exploration, application development, and scenario empowerment. The lag between academic and public attention appears to have narrowed from 18 to 24 months to 6 to 12 months. If confirmed by formal causal analysis, that pattern would suggest that diffusion in design-driven fields involves feedback between academic and public domains rather than a one-way transfer from research to practice. The thematic data are also compatible with a shift in designer competencies from direct making toward orchestrating generative processes, a proposition that awaits larger-sample validation. For researchers, the study offers an analytical approach applicable to other intersections of emerging technology and creative practice.

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