



Systematic Review

AI-Driven Consumer Research in Fashion: A Systematic and Bibliometric Review (2022–2025) and Future Research Agenda

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Abstract

Artificial intelligence (AI) has become a transformative force in fashion e-commerce, reshaping how consumers interact with brands across design, marketing, and retail. However, a systematic synthesis of recent empirical research on consumer interactions with AI in fashion remains underexplored. This study utilizes both systematic and bibliometric approaches to review 50 empirical articles published between 2022 and 2025, retrieved from Scopus and Web of Science, to reveal dominant topics and intellectual structures. Guided by the Theme–Theory–Method (TTM) framework, the review employs systematic content analysis complemented by bibliometric mapping to identify key themes, trends, theories, and methods in existing AI-related consumer studies in fashion. AI-powered chatbots and general AI services are most frequently examined, with the Technology Acceptance Model and Stimulus–Organism–Response framework as leading theoretical lenses. Quantitative research designs prevail, though qualitative and mixed-method approaches are emerging. Based on the findings and identified gaps, a TTM-guided future research agenda is proposed to inform theoretically grounded and practically relevant investigations in the fashion domain, meanwhile contributing to the broader advancement of e-commerce scholarship and practice. This study offers the first integrated synthesis of AI-related empirical consumer research in the contemporary fashion context and the Generative AI era.

Keywords: artificial intelligence; generative AI; fashion; e-commerce; consumer behavior; chatbots; systematic review; bibliometric analysis

1. Introduction

Artificial intelligence (AI) refers to computational systems capable of emulating human cognitive functions such as learning, reasoning, and problem-solving [1]. AI has become a transformative force across industries, including healthcare, education, finance, entertainment, retail, and fashion, reshaping organizational decision-making and value creation for consumers [2,3]. Building on earlier AI developments, Generative AI (GenAI) represents a major advance by enabling machines to produce novel and realistic content, such as text, images, videos, and design concepts, through data-driven learning and pattern recognition [1,4]. Since the release of ChatGPT in 2022, GenAI has attracted significant scholarly and managerial attention for its capacity to automate creativity, scale personalization, and enhance operational efficiency [5,6]. More recently, the emergence of agentic AI in 2025 has marked a shift toward an agent-driven economy, in which autonomous AI systems can anticipate needs, navigate choices, negotiate, and execute multistep actions while remaining aligned with human intent [7].



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Fashion offers a distinctive and theoretically rich context for examining AI-driven consumer behavior, as fashion consumption is closely tied to identity expression, aesthetic judgment, and social meaning [8]. Unlike primarily utilitarian product categories, fashion involves self-expression, body-related evaluation, creativity, and sensitivity to trends, all of which shape consumer responses to AI-mediated interactions [9]. Reflecting these characteristics, the fashion industry has been at the forefront of adopting AI-driven solutions across the value chain, from product design and marketing to customer service and retail experiences [10]. Fashion brands, in particular, have emerged as early adopters of consumer-facing AI applications in e-commerce, driven by intense competition and rapidly evolving consumer expectations, e.g., [5,11]. Together, the symbolic nature of fashion consumption and the rapid diffusion of advanced AI technologies underscore the importance of understanding how consumers perceive, interact with, and adopt AI-driven applications in fashion. Despite growing scholarly interest, systematic syntheses of recent empirical studies capturing consumer experiences in the GenAI era remain limited.

To address this gap, this study conducts a systematic literature review, complemented by bibliometric analysis, to synthesize empirical consumer research on AI in the fashion domain published between 2022 and 2025. A hybrid analytical approach is adopted, in which a structured systematic review guided by the Theme–Theory–Method (TTM) framework serves as the primary lens, while bibliometric techniques map intellectual structures and research trends. The TTM framework is particularly suitable for this interdisciplinary and rapidly evolving field, as it enables a coordinated examination of what consumer phenomena are studied, how they are theoretically explained, and how they are empirically investigated [12]. Organizing the literature along these dimensions facilitates a transparent synthesis of dominant and emerging themes, theoretical foundations, and methodological patterns, while also revealing critical gaps and imbalances. Accordingly, the study is guided by the following research questions:

RQ1: What is the current research landscape, including key themes and emerging trends, within empirical AI-driven consumer studies in the fashion domain (2022–2025)?

RQ2: What theoretical frameworks have been applied, and how have they been used to explain consumer responses to AI-driven fashion retailing contexts?

RQ3: What methodological approaches have been employed, and how have they been designed to investigate AI-related consumer phenomena in fashion?

Collectively, these questions aim to map the scholarly landscape of AI-focused consumer research in fashion, synthesize theoretical and methodological developments, and identify priorities for future research. The findings are expected to deepen understanding of how AI-driven innovations shape consumer experiences and decision-making in fashion contexts, while offering insights for researchers, practitioners, and policymakers seeking responsible, consumer-centric AI integration within the industry.

Contribution Beyond Prior AI–Fashion Reviews

Although several reviews published between 2022 and 2025 have examined AI in fashion-related contexts, their scopes, methodological orientations, and analytical emphases differ substantially from the present study. As shown in Table 1, prior reviews largely focus on specific technologies (e.g., conversational agents or recommender systems), technical architectures, or supply-chain and decision-support perspectives, often without systematically integrating consumer-centric themes, theoretical frameworks, and empirical methods [13–15].

In contrast, this study provides a consumer-centered and empirically bounded synthesis of AI-driven fashion research in the GenAI era (2022–2025). Rather than cataloging technologies or offering speculative projections, this review adopts the TTM framework

to examine what consumer phenomena are studied, how they are theoretically explained, and how they are empirically investigated. Building on this synthesis, the study develops a TTM-informed future research agenda.

Table 1. Comparison of the Present Review with Prior AI–Fashion Reviews (2022–2025).

Study	Review Scope	Methodological Approach	Temporal Focus	Key Emphasis
Manzo, Jiang [13]	AI-based conversational agents in sustainable fashion	Systematic literature review	Primarily pre-GenAI and early GenAI	Examines key techniques, platforms, and application domains of conversational agents in advancing sustainability within the fashion industry.
Shirkhani, Mokayed [14]	AI-driven fashion recommender systems	Technical and system-oriented review	Primarily pre-GenAI and early GenAI	Summarizes recent AI algorithmic performance and architecture in fashion recommender systems.
Pereira, Moura [15]	AI-based decision support in fashion supply chains	Model-driven and analytical review	Pre-GenAI	Explores AI-enabled customer model–recommendation system (CM/RS) combinations supporting decision-making in fashion retail supply chains.
This study	AI-driven consumer research in fashion	Systematic review combined with bibliometric analysis, guided by the TTM framework	2022–2025 (GenAI era)	Provides the first integrated, TTM-guided synthesis of empirical consumer research in fashion, revealing structural landscape across research themes, theoretical foundations, and methodological approaches and proposing a TTM-informed future research agenda.

This review advances prior literature syntheses by adopting a TTM-guided analytic framework designed to prioritize depth, integration, and gap diagnosis rather than descriptive mapping alone. The TTM structure enables systematic analytical depth across three dimensions. First, it supports a nuanced examination of thematic evolution, fragmentation, and cross-theme tensions. Second, it facilitates a critical evaluation of theoretical diversity, dominance, and underexplored perspectives. Third, it allows assessment of methodological concentration, recurring limitations, and emerging innovations. Taken together, this dimensional approach enables the identification of research gaps, conceptual inconsistencies, and conflicting findings that often remain obscured in traditional mapping-oriented reviews.

By explicitly integrating Theme, Theory, and Method, the TTM-guided synthesis provides a multi-dimensional perspective on GenAI-era empirical consumer research in fashion. This integrative structure uncovers cross-dimensional linkages and misalignments, clarifies where theoretical development has not kept pace with thematic expansion, and highlights methodological constraints that impede cumulative knowledge building. Importantly, the framework supports the derivation of both immediate and strategic research priorities, thereby strengthening theoretical advancement while enhancing managerial relevance.

2. Methods

2.1. Literature Search and Selection Process

A structured literature search was conducted using Scopus and the Web of Science Core Collection, two leading multidisciplinary databases widely used in business and social science research. Although partially overlapping, these databases index distinct journals and disciplinary areas, which is critical for capturing the interdisciplinary scope of AI-driven consumer research in fashion [16]. Using both databases enhances bibliometric reliability, enables cross-validation of metadata, and reduces the risk of omitting relevant empirical studies [17]. The review followed the PRISMA 2020 guidelines to ensure transparency and reproducibility throughout the selection process [18].

The final searches were conducted on May 19, 2025, using the same search string in both databases: (TITLE-ABS-KEY(ai OR (generative AND ai) OR (artificial AND intelligence) OR (intelligence) OR (large AND language AND model) OR (machine AND learning)) AND TITLE-ABS-KEY(fashion OR apparel OR clothes OR clothing OR textile* OR outfit OR wardrobe OR garment*)). Filters were applied to include publications from 2022 to 2025, English-language articles only, and peer-reviewed journal articles. Subject-area exclusions (e.g., engineering and materials science) were implemented through database filters to focus on business, social science, and marketing research.

The 2022–2025 period was intentionally selected to capture empirical consumer studies conducted in the post-GenAI inflection era, following the widespread deployment of large language models and multimodal generative systems in late 2022. Only peer-reviewed journal articles reporting empirical consumer research on AI-related applications in the fashion context were included, ensuring methodological rigor, transparent reporting, and validated constructs [12,19]. Conference proceedings were excluded to maintain consistency in peer-review rigor and methodological transparency, as reporting standards and evaluation criteria vary substantially across conferences [12,19]. Excluding industry reports further enhanced comparability and reproducibility.

As illustrated in the PRISMA 2020 [18] flow diagram (Figure 1), the initial search yielded 829 records across both databases. After removing duplicates, titles, and abstracts were screened for relevance, resulting in 101 full-text articles assessed for eligibility. Studies were excluded if they (1) did not examine AI applications in a fashion or apparel context, (2) focused solely on firm-level or supply-chain issues, or (3) did not involve individual consumers as the unit of analysis. Consequently, 51 articles were excluded, primarily due to a lack of consumer focus. The final sample comprised 50 empirical studies. No backward or forward snowballing was conducted, as the two databases provided comprehensive coverage of recent, high-impact empirical research in this domain [16,17]. Overall, this systematic and transparent search strategy yielded a focused and comprehensive corpus of peer-reviewed empirical studies examining AI technologies, fashion contexts, and consumer behavior during the 2022–2025 period.

2.2. Literature Review Approaches

The final dataset comprises 50 peer-reviewed journal articles. This review adopts a hybrid methodological design that integrates a structured systematic literature review guided by the Theme–Theory–Method (TTM) framework with bibliometric analysis. Analytically, the TTM framework enables cross-dimensional interrogation of the literature by examining the alignment among research themes, theoretical frameworks, and methodological approaches. This approach moves beyond descriptive cataloging to reveal patterns of theoretical over-reliance (e.g., repeated application of TAM across heterogeneous AI contexts), methodological inertia, and under-theorized phenomena, thereby supporting theory refinement and future agenda setting.

The systematic review is well-suited to the relatively focused dataset, as it enables close examination and in-depth synthesis of recent empirical studies on AI-driven consumer behavior in the fashion context [20]. In contrast, bibliometric analysis applies quantitative techniques to bibliographic data to uncover publication patterns, intellectual foundations, and thematic structures within a research field [20]. Together, these approaches allow for a comprehensive synthesis that identifies dominant themes, emerging trends, and research gaps, informing theory-driven directions for future research [19].

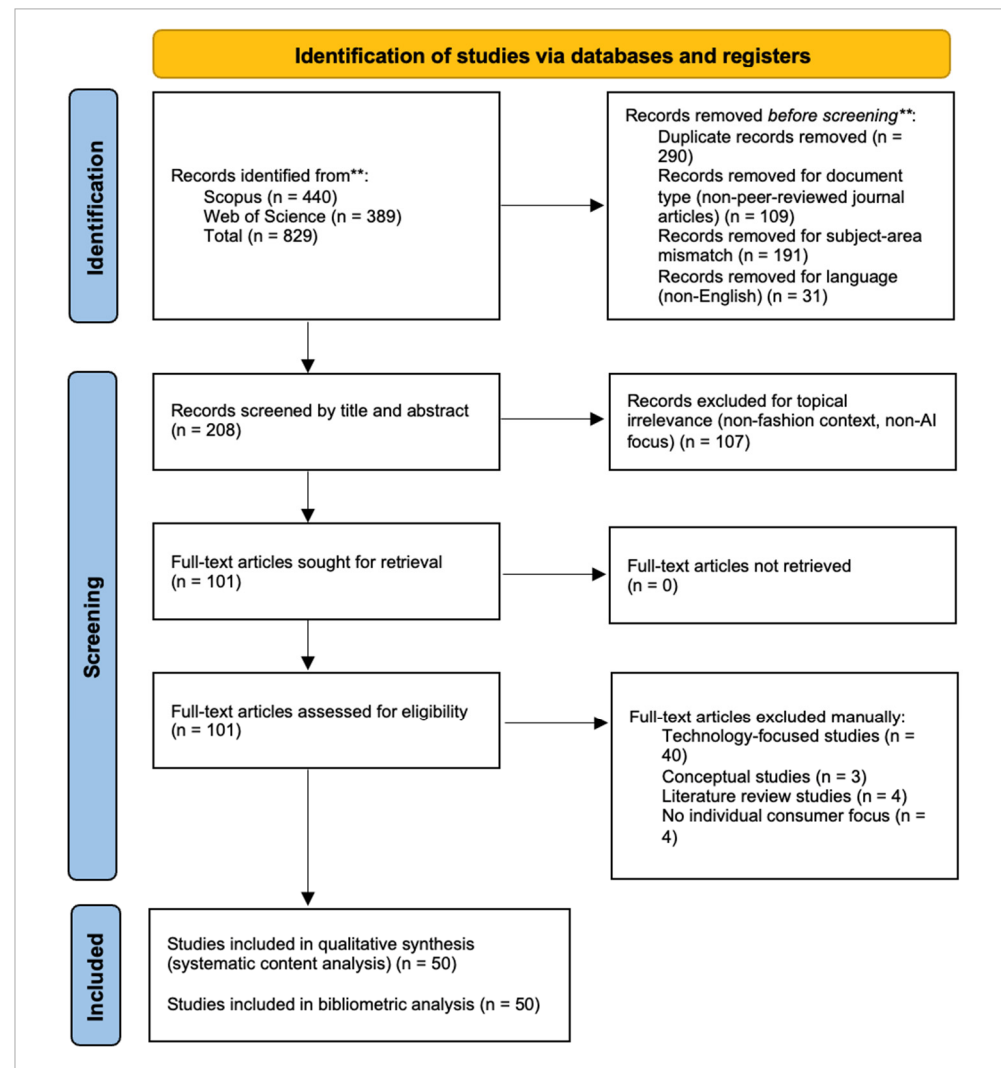


Figure 1. PRISMA 2020 [18] flow diagram of study identification, screening, eligibility, and inclusion. Notes. **, Records were excluded using database-embedded automation filters prior to manual screening.

Guided by the TTM framework, the analysis followed a structured, multi-stage process aligned with the three research questions. For RQ1, inductive thematic content analysis was combined with bibliometric mapping to identify and contextualize major and emerging research themes. Each study was coded based on its focal AI application, core consumer phenomenon, and research context. For RQ2, theoretical frameworks were extracted through in-depth content analysis and categorized according to their explanatory roles, enabling assessment of theoretical concentration and diversity. For RQ3, methodological characteristics were coded based on study design, data sources, and analytical techniques. Integrating insights across themes, theories, and methods provided a holistic understanding of the literature and informed the proposed future research agenda.

To enhance rigor, two researchers independently conducted all coding and analyses, followed by discussions to resolve discrepancies and reach consensus. Validity was further strengthened by presenting interim findings to an external group of scholars and incorporating their feedback. To address RQ1 in greater depth, inductive thematic analysis involved open coding, axial coding, and iterative refinement, resulting in eight higher-order themes. We acknowledge that some studies exhibit conceptual relevance to multiple themes. For analytic consistency, each article was assigned a single dominant theme based on its primary research focus, theoretical emphasis, and central contribution. This decision

was made to ensure interpretive coherence and avoid artificial inflation of thematic frequencies. Importantly, thematic overlaps were systematically documented and incorporated into the qualitative synthesis, where cross-theme linkages, conceptual intersections, and boundary-spanning insights were explicitly considered. This approach balances classificatory clarity with conceptual sensitivity, while minimizing potential distortion arising from rigid categorization.

Thematic findings were triangulated with bibliometric analyses using two visualization tools: a Thematic Analysis Matrix, based on co-word analysis to assess thematic centrality and density [21], and a Conceptual Structure Map generated through Multiple Correspondence Analysis (MCA) to visualize relationships among key concepts [20,21]. Bibliometric analyses were conducted using R, and publication performance indicators for the included studies are reported to ensure transparency and alignment with the research questions.

To reduce the risk of reporting bias, we reviewed the breadth of our search strategy, which drew from two major databases and included all English-language publications. Furthermore, we recognize that studies reporting positive outcomes, particularly in general AI applications, may be more common in the published literature due to common publication tendencies. No sensitivity analyses were conducted, as the narrative synthesis focused on patterns rather than pooled effects.

This review was retrospectively registered in the OSF Registries (Generalized Systematic Review Registration) on November 29, 2025. Prospective registration was not undertaken because the study was exploratory and conducted without external funding. The registration documents the finalized methods and analyses for transparency; all materials are publicly available via the OSF project (<https://osf.io/4p6z8> accessed on 29 November 2025) and are currently under embargo during peer review until 18 May 2026. No amendments were made after registration.

2.3. Risk of Bias and Certainty Assessment

To enhance the rigor of our synthesis, risk of bias (RoB) in included studies was assessed using the Mixed Methods Appraisal Tool (MMAT) version 2018, suitable for the mixed quantitative-qualitative designs prevalent in consumer behavior research [22]. Two reviewers independently evaluated each of the 50 studies across relevant MMAT criteria (e.g., appropriate sampling for qualitative; valid measurements for quantitative; integration for mixed-methods), achieving consensus through discussion. RoB was rated as low, moderate, or high overall per study. No automation tools were used. This assessment informed the synthesis by weighting interpretations toward low-RoB studies where possible.

Certainty in the synthesized evidence was evaluated using an adapted GRADE-CERQual approach for qualitative and mixed-method findings and the GRADE framework for quantitative themes [23]. Confidence in each identified research stream was rated as high, moderate, low, or very low based on methodological limitations, relevance, coherence, and data adequacy. Two reviewers conducted these assessments independently and reached consensus through discussion.

2.4. Publication Performance Characteristics of Selected Literature

A bibliometric analysis of the final dataset, comprising 50 journal articles on AI-related empirical consumer research in the fashion domain, is conducted. The dataset represented contributions from 124 authors across 37 academic journals. Publication trends over time showed a gradual increase: 9 articles in 2022, 11 in 2023, 22 in 2024, and 8 in early 2025, reflecting growing scholarly interest in this area.

Among the journals, the International Journal of Retail & Distribution Management and the Journal of Retailing and Consumer Services were the most prolific, each contributing four articles to the sample. At the author level, Kautish P., Khare A., Kim H. Y., and Lee G. were the most productive, each publishing three articles. Geographically, the United States emerged as the leading contributor, publishing nine articles, followed by China with five. In terms of scholarly influence, the United States also achieved the highest citation impact, with India ranking second.

3. Findings and Discussions

3.1. Thematic Research Landscape

Table 2 summarizes the key findings from the thematic content analysis by categorizing the 50 reviewed articles into eight major research themes and documenting their distribution over time. For each theme, the table reports the number of studies, core subtopics, publication periods, and corresponding references, providing a concise overview of how AI applications shape consumer experiences, innovation trajectories, and scholarly attention within the fashion domain.

Table 2. Thematic content analysis outcomes.

Research Theme Area	Research Focus	References
AI-powered chatbots (14) Certainty Rating: Moderate	AI-driven chatbots as stylists (1, 2025); AI chatbot service with visual search capability (1, 2025); Social media AI chatbots (3, 2022, 2024); Chatbot service in luxury consumption (1, 2024); Consumer response to chatbot services (4, 2022–2024); Voice-based AI chatbots (3, 2023); Investigate conditions that enable to optimize AI chatbot services (1, 2022)	Ranjan and Upadhyay [24], Qi, Ko [25], Kang, Lee [26], Kang and Choi [27], Shahzad, Xu [28], Myin and Watchravesringkan [29], Mpinganjira, Dlodlo [30], Jin and Youn [31], Li, Wu [32], Kautish, Purohit [33], Huh, Whang [34], Oncioiu [35], Jansom, Srisangkajorn [36], Lou, Kang [37]
AI applications in general (12) Certainty Rating: Moderate	Consumers' responses to AI-powered fashion services (6, 2022–2025); AI's impact on luxury fashion consumption (2, 2023, 2025); AI's influence on Gen Z consumers (2, 2024); GAN-fashion retailing (1, 2024); AI's impact on consumers' omnichannel experiences (1, 2023)	Shin and Yang [38], Khamoushi Sahne and Kalantari Daronkola [39], Ruiz-Viñals, Pretel-Jiménez [40], Das and Das [41], Pandey, Dhaliwal [42], Calvo, Franco [3], Guerra-Tamez, Kraul Flores [43], Khare, Kautish [44], Yeo, Tan [11], Araújo, Gonçalves [2], Rahman, Bag [45], Kautish and Khare [46]
AI-driven recommendations (8) Certainty Rating: Moderate	Compare AI Tools and Human Influencers (1, 2025); Wardrobe management (3, 2022–2025); New recommendation engines (2, 2023, 2024); Digital human stylists (1, 2024); AI-curation subscription services (1, 2023)	Gerlich [47], Jiang and Macintyre [48], Kim and Lehmann [49], Bonetti, Silva [50], Sasanuma and Yang [51], Im and Lee [52], Kim, Kang [53], Bang and Su [54]
AI-assisted product design and development (5) Certainty Rating: Low	Consumer responses to AI-designed products (3, 2024–2025); Consumer perceptions of AI-designed luxury products (2, 2022, 2024)	Lee and Kim [55], Zhang and Liu [8], Lee and Kim [56], Pantano, Serravalle [4], Xu and Mehta [57]
AI-powered virtual influencer (3) Certainty Rating: Low	Consumer responses to virtual influencer recommended products (2, 2023–2024); Consumer perceptions of AI influencers (1, 2024)	Cheng and Wang [58], Toyib and Paramita [59], Almasri [60]
Smart clothing (3) Certainty Rating: Moderate	Consumer responses and acceptance of smart clothing (3, 2023–2024)	Li, Song [61], Arachchi and Samarasinghe [62], Chen and Ye [63]
AI applications in physical stores (3) Certainty Rating: Moderate	AI-enabled personalization service in physical retailing (1, 2024); AI technology in connected retail environments (1, 2024); Retail Service Robot (1, 2022)	Canhoto, Keegan [64], El Abed and Castro-Lopez [65], Song and Kim [66]
AI-driven marketing content generation (2) Certainty Rating: Low	GenAI-generated brand images (1, 2024); AI-generated fashion models (1, 2024)	Park and Ahn [67], Sands, Demsar [68]

Notes: Themes ordered by study count; all studies accounted for (n = 50).

Table 2 also reports certainty ratings, reflecting the depth, consistency, and methodological quality of evidence across themes. AI-powered chatbots, general AI applications, AI-driven recommendations, smart clothing, and in-store AI received moderate certainty ratings, supported by a larger and more consistent body of studies with generally lower

risk of bias. In contrast, AI-assisted product design, virtual influencers, and AI-generated marketing content were rated low certainty, as these streams remain smaller, more recent, and narrower in empirical scope.

Figures 2 and 3 complement the content analysis through bibliometric visualization. The Thematic Analysis Matrix (Figure 2), based on co-word analysis, organizes themes by centrality and density, distinguishing motor themes (e.g., chatbots), basic themes (e.g., customer experience), emerging themes (e.g., generative AI), and niche themes (e.g., artificial intelligence). This structure highlights differences in thematic maturity and scholarly relevance.

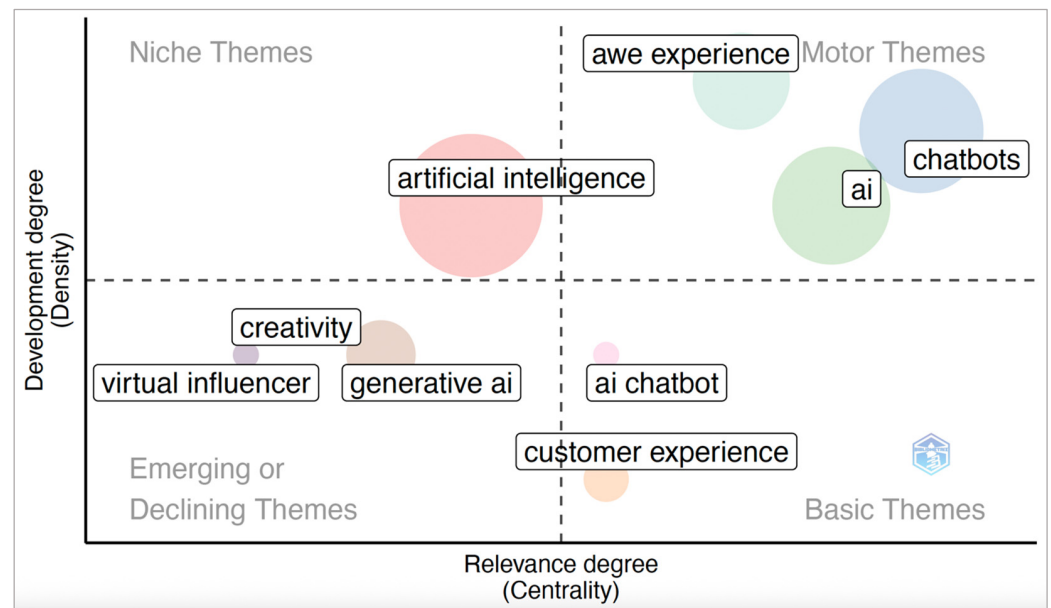


Figure 2. Thematic Analysis Matrix.

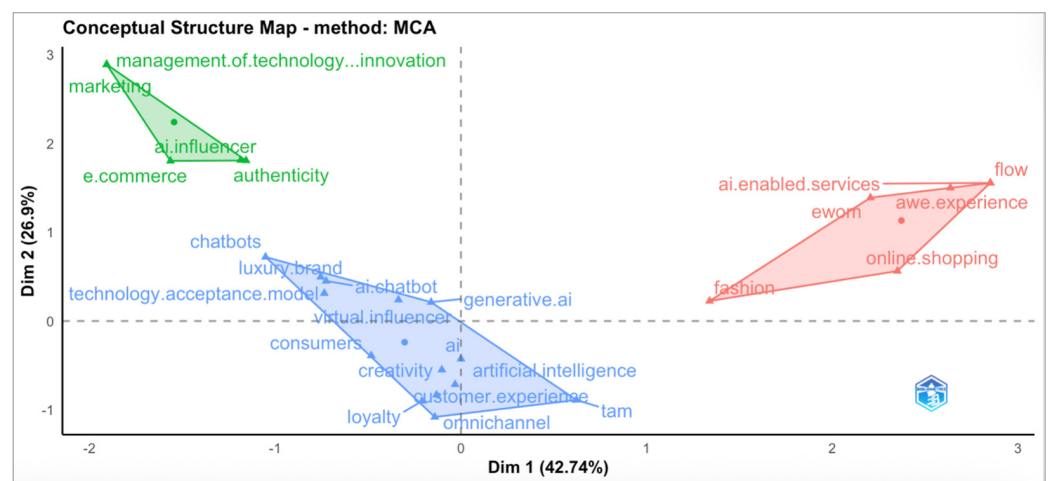


Figure 3. Conceptual Structure Map.

The Conceptual Structure Map (Figure 3), generated using MCA, reveals three thematic clusters. Cluster 1 (green) captures marketing and technology management research, particularly studies on virtual influencers and authenticity in e-commerce contexts. Cluster 2 (blue), the largest cluster, centers on AI-enabled product–service hybrids, including chatbots, luxury branding, and technology acceptance, reflecting research on consumer perceptions, trust, and loyalty. Cluster 3 (red) represents general AI-enabled service research, emphasizing affective and experiential responses such as flow and awe. Together,

the two extracted dimensions explain 69.64% of the total variance, indicating a well-defined conceptual structure.

Integrating content and bibliometric analyses yields three overarching insights. First, AI-powered chatbots emerge as the most prominent theme (14 studies), reflecting their central role in fashion retailing. Early research (2022–2024) focused on rule-based chatbots and emphasized usability, trust, and satisfaction, often drawing on social presence and anthropomorphism-related theories, e.g., [28,33,36]. More recent studies (2025) shift toward GenAI-enabled, multimodal chatbots, including visual search and virtual styling, highlighting value co-creation, engagement, and perceived ownership through iterative personalization [24,25]. Bibliometric evidence reinforces this centrality, positioning chatbots as both a motor and basic theme and situating them at the core of the largest conceptual cluster, while also revealing underexplored issues such as long-term loyalty and ethical risks.

Second, general AI-enabled services constitute the second-largest theme (12 studies), with a strong emphasis on experiential outcomes. Research in this stream examines consumer responses across omnichannel journeys, luxury contexts, and generational segments, frequently highlighting affective mechanisms such as awe and flow, e.g., [44,46]. Bibliometric patterns place these studies within a prominent conceptual cluster and identify “awe experience” as a motor theme. At the same time, broader constructs such as customer experience remain underdeveloped, suggesting a gap between general AI discourse and fine-grained, consumer-centered theorization.

Third, the remaining 24 articles span six supplementary streams: AI-driven recommendations, AI-assisted product design, virtual influencers, in-store AI, smart clothing, and AI-generated marketing content, reflecting the growing diversification of AI applications in fashion. Recommendation studies emphasize personalization and decision support while raising concerns about authenticity and autonomy, e.g., [51–53]. Creative and influencer-oriented AI research highlights tensions around authorship, human-likeness, and ethical persuasion, e.g., [58,59]. In-store AI and smart clothing studies explore immersion, usability, and privacy trade-offs, e.g., [61,64,65], while AI-generated marketing content research underscores efficiency and inclusivity alongside authenticity risks [67,68]. Bibliometric dispersion across clusters underscores the fragmented yet rapidly evolving nature of these streams. The Thematic Analysis Matrix identifies “generative AI,” “virtual influencer,” and “creativity” as emerging themes, while the Conceptual Structure Map positions these applications across both the product-service hybrid cluster (Blue) and the marketing innovation cluster (Green).

Overall, triangulating thematic and bibliometric evidence reveals a coherent but still formative intellectual structure. Established themes such as chatbots and experiential AI services show conceptual maturity and centrality, whereas generative, creative, and influencer-oriented applications remain emergent and under-consolidated. This pattern highlights substantial opportunities for theoretical extension, methodological innovation, and deeper integration across product, service, and marketing domains in future AI-driven fashion research.

3.2. Theoretical Landscape

To address RQ2, theory-driven content analysis identified 22 theoretical frameworks used across the reviewed studies (see Table 3), each offering a distinct explanatory lens. The Technology Acceptance Model (TAM) is the most frequently applied framework, appearing in eight studies. TAM emphasizes perceived usefulness and ease of use as key determinants of attitudes and behavioral intentions toward AI-powered fashion applications and has been widely used to examine the adoption of general AI services [38,40], chatbots [28,35], smart clothing [62,63], and AI-driven stylists [50]. The Stimulus–Organism–Response (SOR)

framework, employed in six studies, provides a broader perspective by explaining how AI-related stimuli, such as service design, personalization, and anthropomorphism, shape internal states (e.g., trust, satisfaction, emotional engagement) that subsequently influence behavioral outcomes such as loyalty and word-of-mouth, e.g., [28,39].

Table 3. Summary of Theories, Key Constructs, and References.

Theory/Framework	Key Constructs	References	Frequency
Technology Acceptance Model (TAM) [1]	Perceived usefulness, ease of use, attitude, and behavioral intention	Bonetti, Silva [50], Oncioiu [35], Chen and Ye [63], Qi, Ko [25], Shin and Yang [38], Li, Song [61], Myin and Watchravesringkan [29], Khamoushi Sahne and Kalantari Daronkola [39]	8
Stimulus–Organism–Response (SOR) [2]	Service quality, trust, Word-of-Mouth (WOM), anthropomorphism, experiential value, and awe experience	Shahzad, Xu [28], Mpinganjira, Dlodlo [30], Khare, Kautish [44], Rahman, Bag [45], Kautish, Purohit [33], Khamoushi Sahne and Kalantari Daronkola [39]	6
Broaden-and-Build Theory (BBT) [3]	Flow, awe experience, and WOM	Pandey, Dhaliwal [42], Kautish and Khare [46], Kautish, Purohit [33]	3
Functional–Expressive–Aesthetic Model (FEAM) [4]	Functionality, expressiveness, and aesthetics	Chen and Ye [63], Li, Song [8,61]	3
Attribution Theory (AT) [5]	Intrinsic/extrinsic motivation, authenticity, and social identity threat	Cheng and Wang [58], Sands, Demsar [68]	2
Mind Perception Theory (MPT) [6]	Experience, agency, and AI threat	Lee and Kim [55], Ranjan and Upadhyay [24]	2
Hedonic Information Systems Acceptance Model (HISAM) + Technology Readiness [7]	Perceived intelligence, automation, and personalization	Arachchi and Samarasinghe [62]	1
Theory of Consumption Value (TCV) [8]	Functional, emotional, epistemic, social, and conditional values	Das and Das [41]	1
Behavioral Reasoning Theory (BRT) [9]	Optimism, complexity, innovativeness, and advantage	Myin and Watchravesringkan [29]	1
Uses and Gratifications Theory (UGT) [10]	Service quality, empathy, and informational value	Kang and Choi [27]	1
Value Co-creation Theory (VCT) [11]	Anthropomorphism, credibility, and empathy	Ranjan and Upadhyay [24]	1
Affect–Behavior–Cognition (ABC) Model [12]	Hedonic motivation, attitude, and WOM	Kang, Lee [26]	1
Computers-Are-Social-Actors theory (CASA) [13]	Usefulness, capability, and robot anxiety	Song and Kim [66]	1
Media Equation Theory (MET) [14]	Human-likeness, social roles, and use autonomy	Huh, Whang [34]	1
Self-Verification Theory (SVT) [15]	Self-brand congruence, brand personality	Park and Ahn [67]	1
Engel-Kollat-Blackwell (EKB) Model [16]	Value, quality, risk, price, and emotional experience	Yeo, Tan [11]	1
Personalization-Privacy Paradox (PPP) [17]	Personalization, autonomy	Canhoto, Keegan [64]	1
Theory of Stereotyping (TS) [18]	Perceived creativity	Im and Lee [52]	1
Schema Theory (ST) [19]	Perceived authenticity, product fit	Lee and Kim [56]	1
Goal-Derived Theory (GDT) [20]	Gain goal, hedonic goal, and normative goal	Kim, Kang [53]	1
Technology Readiness and Acceptance Model (TRAM) [21]	Customer engagement, digital multisensory cues	Rahman, Bag [45]	1
Fishbein’s Attitude Theory (FAT) [22]	Socially responsible consumption behavior, personal innovativeness in information technology, and attitude toward virtual wardrobes	Bang and Su [54]	1

Three studies draw on the Broaden-and-Build Theory (BBT) to explain how positive emotions, including awe and flow, foster engagement and experiential loyalty in AI-driven

fashion retailing, e.g., [33,42]. The Functional–Expressive–Aesthetic Model (FEAM), also used in three studies, captures the functional, symbolic, and aesthetic drivers of fashion adoption and has been applied primarily to smart clothing and AI-assisted fashion design contexts [8,61,63]. Two theories appear twice in the dataset. Attribution Theory (AT) examines how consumers infer the intentions behind AI-generated messages, shaping perceptions of genuineness or manipulation, particularly in studies of virtual influencers and AI-generated advertising [58,68]. Mind Perception Theory (MPT) explains how consumers attribute agency and experience to AI entities, influencing perceptions of authenticity, competence, and threat in creative domains such as fashion design and chatbot-based styling services [24,56].

Beyond these recurring frameworks, 16 theories are applied only once, reflecting high theoretical dispersion. These include the Hedonic Information Systems Acceptance Model (HISAM), extended with technology readiness, to explain intelligent clothing adoption [62]; the Theory of Consumption Value (TCV), used to assess how emotional, social, and epistemic values drive purchase intentions in AI-enabled retailing [41]; and Behavioral Reasoning Theory (BRT), which captures the tension between adoption and resistance by incorporating reasons for and against AI use [29]. Other single-use frameworks include Uses and Gratifications Theory (UGT) [27], Value Co-Creation Theory (VCT) [24], the Affect–Behavior–Cognition (ABC) model [26], Computers Are Social Actors (CASA) theory [66], and Media Equation Theory (MET) [34], each applied to explain specific interaction mechanisms in chatbot or in-store AI contexts.

Additional theories address branding, identity, and decision-making processes. Self-Verification Theory (SVT) explains preferences for AI-generated brand personalities aligned with consumers' self-concepts [67], while the Engel–Kollat–Blackwell (EKB) model has been used to examine AI-supported fashion purchase decisions on social media platforms [11]. The Personalization–Privacy Paradox (PPP) guides research on trade-offs between personalization benefits and privacy concerns in physical retail environments [64]. Schema Theory (ST) and Theory of Stereotyping (TS) explain how preexisting mental models shape evaluations of AI creativity and authenticity [52,56]. Finally, Goal-Derived Theory (GDT) [53], Fishbein's Attitude Theory (FAT) [54], and the Technology Readiness and Acceptance Model (TRAM) combined with SOR [45] offer additional insights into AI-driven recommendations and luxury online shopping experiences. Overall, these frameworks provide a broad theoretical foundation for understanding consumer perceptions, interactions, and responses to AI in fashion retailing, while also revealing substantial variation in theoretical concentration and maturity across research streams.

3.3. Methodological Landscape

Method-oriented content analysis of the 50 empirical studies (see Table 4) reveals a clear predominance of quantitative designs (39 studies), followed by mixed-method (6) and qualitative approaches (5). This distribution reflects a strong emphasis on empirical validation and generalizability, primarily achieved through structured online surveys and experiments. Data were most commonly collected via research firms and consumer panels, with additional use of convenience sampling and social media sources, indicating an increasing commitment to data reliability and methodological rigor.

Five of the eight identified research streams demonstrate methodological diversity, incorporating quantitative, qualitative, and mixed-method designs, which signals growing methodological maturity. In particular, studies on AI-powered chatbots, general AI applications, AI-driven recommendation systems, and AI-assisted product design employ a range of methods, including surveys, experiments, interviews, focus groups, action research, and big data analysis, to capture diverse consumer responses in AI-driven fashion contexts.

In contrast, research on virtual influencers, smart clothing, and AI-generated marketing content relies almost exclusively on quantitative surveys and experiments using consumer panel data, reflecting the early empirical stage of these streams.

Table 4. Key findings of the methodological landscape.

Research Streams	Research Method and Design	Data Collection
AI-powered chatbots (14)	- Quantitative: Online survey (10), Online experiment (2) - Qualitative: Interview (1) - Mixed: Interview + Online survey (1)	- Social media data (2) - Convenience sample data (2) - Consumer panel data (10)
AI applications in general (12)	- Quantitative: Online survey (9) - Qualitative: Interview (1) - Mixed: Interviews + Online survey (1), - Focus group + Online survey (1)	- Convenience sample data (2) - Consumer panel data (10)
AI-driven recommendations (8)	- Quantitative: Online survey (5), Online experiment (1) - Qualitative: Big data mining and analysis (1) - Mixed: Interview + Online survey (1)	- Social media data (1) - Convenience sample data (1) - Social media + convenience sample data (1) - Consumer panel data (5)
AI-assisted product design and development (5)	- Quantitative: Online experiments (3) - Qualitative: Interview (1) - Mixed: Action research + online survey (1)	- Convenience sample data (1) - Consumer panel data (4)
AI-powered virtual influencer (3)	Quantitative: Online survey (2), Online survey + online experiments (1)	Consumer panel data (3)
Smart clothing (3)	Quantitative: Online survey (3)	Consumer panel data (3)
AI applications in physical stores (3)	- Quantitative: Field experiment (1) - Qualitative: Interview (1) - Mixed: Interview + Online survey (1)	- Convenience sample data (1) - Consumer panel data (2)
AI-driven marketing content generation (2)	Quantitative: Online survey (1), Online experiment (1)	Consumer panel data (2)
Total research articles (50)	- Quantitative: 39 - Qualitative: 5 - Mixed: 6	- Social media data: 3 - Convenience sample data: 7 - Social media + convenience sample data: 1 - Consumer panel data: 39

Notes: 32 studies low RoB, 16 moderate, 2 high; high RoB primarily in early qualitative designs due to small samples.

Despite increasing methodological breadth, most studies continue to rely on cross-sectional survey designs. While suitable for early theory testing, these approaches provide limited insight into causal mechanisms and dynamic processes. Notably, the literature overwhelmingly tests linear main effects, despite indications that consumer responses to AI, such as trust, anthropomorphism, and personalization, vary by context, user characteristics, and perceived autonomy. The limited use of moderators, interaction effects, and non-linear modeling constrains the field's ability to reconcile inconsistent findings. Qualitative

methods remain underutilized and are rarely integrated with quantitative analyses, despite their potential to illuminate complex issues such as agency, authenticity, and ethical concern.

Overall, the methodological landscape reflects a field that prioritizes efficiency and early validation over analytical depth. Advancing AI-driven fashion research will require greater use of longitudinal designs, behavioral data, mixed-method approaches, and non-linear modeling to capture the relational and context-sensitive nature of consumer-AI interaction. Because this review relies on narrative synthesis, formal statistical assessments of reporting bias were not feasible; however, the diversity of reported outcomes and geographic coverage suggests a relatively low risk of systematic reporting bias.

3.4. Overall Research Landscape and Discussion

This section integrates findings from the thematic, theoretical, and methodological analyses using the Theme–Theory–Method (TTM) framework to provide a consolidated overview of AI-related empirical consumer research in the fashion domain during the GenAI era (see Table 5). The synthesis highlights not only what has been extensively studied, but also where research remains underdeveloped. By aligning research themes with their dominant theories and methods using consistent dominance criteria, the analysis reveals structural imbalances in the literature. Although AI technologies have diversified rapidly, empirical research has not fully adapted to capture the resulting complexity of consumer-AI interactions.

Table 5 synthesizes evidence across themes, theories, and methods to surface patterns that extend beyond descriptive mapping. The TTM-based analysis identifies areas where empirical attention has outpaced theoretical development, where established theories are applied without sufficient contextual sensitivity, and where methodological homogeneity constrains explanatory depth. These misalignments are not readily visible in theme-only or theory-focused reviews, underscoring the analytic value of the TTM framework for diagnosing limitations and guiding future research.

The TTM-guided analysis functions diagnostically, revealing not only research gaps but also cross-theme tensions, theoretical blind spots, and contradictions in empirical findings that constrain cumulative knowledge development. Importantly, while each study was assigned a single dominant theme for analytic clarity, thematic overlaps were systematically documented and incorporated into the qualitative synthesis. This approach enabled the identification of cross-theme linkages, conceptual intersections, and boundary-spanning patterns that would remain less visible under rigid classification. The resulting synthesis, therefore, reflects both classificatory consistency and interpretive integration.

Across research streams, three analytic patterns emerge. First, the literature exhibits recurring cross-theme tensions, wherein design features or AI capabilities intended to enhance consumer value simultaneously generate countervailing psychological or evaluative responses. Second, the review identifies persistent theoretical blind spots, particularly the limited capacity of dominant adoption- and evaluation-oriented frameworks to explain identity-relevant judgments, legitimacy concerns, and delegated agency dynamics. Third, the synthesis reveals structured contradictions in empirical findings, most prominently surrounding the constructs of anthropomorphism, authenticity, and autonomy. These contradictions do not represent isolated inconsistencies but rather signal unresolved conceptual tensions central to consumer–AI interaction in fashion contexts.

Table 5. Synthesis of TTM-guided major findings.

Research Theme	Theories Employed and Frequently Used Variables	Dominant Theories Used	Dominant Methods Used	Key Limitations and Research Gaps
AI-powered chatbots	TAM, SOR, VCT, MPT, UGT, ABC, BRT, BBT; anthropomorphism	TAM, SOR	Online survey; online experiment	Overemphasis on adoption and satisfaction; limited relational depth, ethical reflection, and longitudinal evidence; underdeveloped research on GenAI-enabled and multimodal chatbot features
AI applications in general	TAM, SOR, BBT, TCV, EKB, TRAM; awe, flow	TAM, SOR, BBT	Online survey	Broad and abstract treatment of AI; weak fashion specificity; AI often operationalized as a generic service rather than concrete fashion applications
AI-driven recommendations	TAM, TS, GDT, FAT	N/A	Online survey	Limited behavioral validation; underexplored research on consumers' trade-offs (e.g., perceived benefits and risks, autonomy, transparency, and trust calibration)
AI-assisted product design and development	MPT, FEAM, ST	N/A	Online experiment	Limited attention to authorship, ownership, ethics, and human–AI co-creation boundaries
AI-powered virtual influencers	AT; anthropomorphism, authenticity	N/A;	Online survey	Limited cultural and longitudinal perspectives; underdeveloped theorization of authenticity and persuasion
Smart clothing	TAM, FEAM, HISAM + Technology Readiness	TAM, FEAM	Online survey	Predominantly adoption-focused; limited exploration of embodied experience, daily use, and post-adoption outcomes
AI applications in physical stores	CASA; personalization, privacy	N/A	N/A	Fragmented evidence base; insufficient replication of methods; limited integration of omnichannel journeys and contextual retail dynamics
AI-driven marketing content generation	AT, SVT	N/A	N/A	Very limited empirical base; underexplored governance, bias, inclusivity, and long-term brand implications

Notes: Dominant theories refer to theoretical frameworks applied in two or more empirical studies within the same research theme; Dominant methods refer to research methods used in two or more empirical studies within the same research theme; N/A indicates it does not meet the dominance threshold for that theme.

3.4.1. Asymmetric Theoretical Anchoring Across Research Themes

Table 5 reveals clear asymmetries in theoretical anchoring across research themes. AI-powered chatbots and general AI applications consistently rely on established frameworks such as TAM and SOR, whereas themes including AI-driven recommendations, AI-assisted product design, virtual influencers, and AI-generated marketing content lack dominant theoretical anchors, reflecting fragmented and exploratory theorization. This pattern signals uneven epistemic maturity rather than mere theoretical dispersion. Themes with recurring theory use typically involve stable interaction paradigms (e.g., adoption and service evaluation), while creative, symbolic, or agentic AI applications raise concerns, such as authorship, authenticity, autonomy, and social meaning, which are not well captured by existing models.

Specifically, adoption-oriented frameworks appear well-suited to contexts emphasizing efficiency, usability, and service functionality. However, when AI systems become implicated in symbolic consumption, creative authorship, or identity construction, consumers engage evaluative processes that extend beyond perceived usefulness or experiential response. Thematic overlaps across creative AI, influencer AI, and recommendation systems

highlight the growing salience of authenticity, legitimacy, and autonomy-related judgments, which remain only partially accommodated within dominant theoretical models.

Three factors explain this limited theoretical convergence. First, AI applications differ not only technologically but also phenomenologically: adopting a chatbot, evaluating an AI-designed garment, and engaging with a virtual influencer activate distinct cognitive, affective, and identity-related processes. Second, the literature prioritizes novelty and application diversity, encouraging theory borrowing over cumulative development. Third, the rapid shift from predictive to generative and agentic AI has outpaced theory refinement, favoring exploratory work over replication. From a TTM perspective, dispersion thus reflects conceptual instability, indicating where consolidation is premature and where deeper theorization is needed.

3.4.2. AI-Powered Chatbots: Theoretical Consolidation and Emerging Tensions

AI-powered chatbots are the most extensively studied stream and illustrate both consolidation and dispersion. As shown in Table 5, eight theories are applied, but only TAM and SOR recur sufficiently to qualify as dominant. TAM-based studies emphasize perceived usefulness and ease of use, particularly for routine information search and shopping support, e.g., [25,35]. SOR-based research treats chatbot features, most notably anthropomorphism, along with responsiveness and personalization, as stimuli shaping trust, enjoyment, and experiential value, which in turn influence loyalty, continuance intention, and electronic word-of-mouth, e.g., [28,30]. Empirical findings are broadly positive across text-based, voice-based, social media, and stylist chatbots, e.g., [28–30,36].

However, the accumulated evidence is also marked by a reproducible contradiction: anthropomorphism is frequently beneficial, yet it does not behave as a uniformly positive design lever. Across studies, human-likeness can enhance social presence, imagery processing, psychological ownership, and trust [31,32,34]; at the same time, more socially charged cues can fail to translate into better decisions or can even depress continuance when they are experienced as intrusive or socially demanding, e.g., [30]. Importantly, this contradiction is not simply “mixed results”, and it reflects a tension between relational enrichment and relational risk. In fashion contexts, where social identity and self-presentation are salient, human-like cues may heighten the felt sociality of the interaction, but they also raise consumers’ sensitivity to manipulation, norm violations, or uncanny dissonance. This pattern implies that anthropomorphism is better conceptualized as a boundary-sensitive mechanism rather than a linear stimulus that reliably increases positive outcomes.

Two theoretical blind spots follow. First, chatbots are still largely modeled as functional tools rather than relational or agentic participants embedded in ongoing consumer–brand relationships, e.g., [28,30]. Second, as chatbots become GenAI-enabled, multimodal, and more autonomous, normative concerns, including persuasion, transparency of agency, privacy disclosure, reliance formation, and long-run dependence, remain under-theorized, e.g., [24,25]. The stream has begun to surface the right questions, but prevailing models are more effective at explaining initial comfort and usefulness than how consumer trust, control, and reliance evolve as chatbots take on more proactive roles.

3.4.3. AI Applications in General: Experiential Focus and Conceptual Ambiguity

Research on AI applications in general is the second most developed stream, but also the most conceptually ambiguous. Unlike chatbot studies, this stream often treats AI as a broad service capability rather than a specific technological configuration. Empirical findings consistently show positive effects on purchase intention, engagement, trust, and loyalty when AI is perceived as intelligent and seamlessly integrated, e.g., [3,39,44,45], typically explained through TAM and SOR. Some studies incorporate affective constructs

such as awe and flow, drawing on BBT or EKB to explain experiential loyalty and word-of-mouth, e.g., [11,42,46].

However, experiential richness often comes at the cost of conceptual clarity. AI is frequently operationalized as a generalized “smart service,” blurring distinctions among recommendation, generative, predictive, and conversational systems and limiting comparability and theory accumulation. As a result, dominant adoption-oriented theories can appear to “work” while quietly absorbing heterogeneous phenomena that likely depend on different mechanisms. This stream also exposes a key cross-theme tension: as AI becomes embedded across the consumer journey, it can elevate perceived convenience and engagement while simultaneously intensifying opacity, power asymmetry, and vulnerability—conditions that would plausibly amplify autonomy and privacy concerns, e.g., [2,38,40,45]. Yet existing frameworks offer limited insight into trust recalibration, reliance development, or consumer boundary management under repeated and increasingly agentic AI encounters.

3.4.4. AI-Driven Recommendations: Navigating Perceived Value and Consumer Concerns

AI-driven recommendation research focuses on personalization, decision facilitation, and efficiency, yet remains comparatively under-theorized. Studies show that AI-powered recommendations enhance relevance, reduce decision fatigue, and improve shopping experiences, e.g., [47,51,53], and may support sustainability and well-being through wardrobe management and reuse [48,54]. These benefits are typically explained through adoption- or goal-oriented frameworks.

A recurring contradiction is that recommendations can be judged as highly competent yet comparatively less authentic, emotionally resonant, or creatively appropriate than human advice, especially in fashion categories where symbolic meaning and taste expression matter [47,50,52]. Consumers may welcome AI for efficiency but hesitate when the decision becomes identity-laden or when creativity is expected [51,52]. This implies that “value” in recommendation contexts is not reducible to accuracy or convenience; it depends on whether the system is perceived as supporting consumer agency versus substituting it. Yet much of the literature treats personalization as unambiguously beneficial and leaves autonomy concerns implicit. Theoretical blind spots are therefore pronounced: delegated decision-making, transparency of recommendation logic, perceived control, and long-term consequences for identity and taste formation are often noted but not modeled as central mechanisms. The stream would benefit from moving beyond short-term adoption outcomes to account for how consumers negotiate control, legitimacy, and self-expression when AI becomes an influential advisor.

3.4.5. Creative and Influencer-Oriented AI: Authenticity, Agency, and Symbolic Tensions

Research on AI-assisted design, virtual influencers, and AI-generated marketing content operates in highly symbolic, identity-relevant domains. Here, the literature converges around a contradiction centered on authenticity: AI involvement can increase novelty and perceived sophistication, yet it can also undermine authenticity, emotional resonance, and brand essence, especially once AI authorship is disclosed [4,55–57]. Evidence that customization can mitigate negative reactions is particularly revealing [4], as it suggests that consumers may not reject AI creativity per se, but they resist when AI creativity is experienced as detached from human intention or as misaligned with identity work.

A second contradiction links authenticity and anthropomorphism. Virtual influencers and AI-generated content often benefit from human-likeness and perceived authenticity [59,60], but these same features can trigger resistance when endorsement is interpreted as illegitimate, opaque, or socially inauthentic [58,67,68]. This tension underscores a theo-

retical blind spot: service and adoption theories often treat authenticity as an evaluative outcome rather than as an interpretive judgment rooted in cultural expectations about human creativity, moral legitimacy, and symbolic authority. In these domains, consumers are not merely assessing “AI performance”; they are negotiating what counts as real, credible, and appropriately human in fashion communication and creation.

3.4.6. Wearable and In-Store AI: Embodiment, Surveillance, and Privacy Trade-Offs

Wearable and in-store AI studies show greater reliance on established adoption frameworks (e.g., TAM and FEAM), especially when explaining initial interest based on usability, aesthetics, and functional benefits, e.g., [61,63]. Yet the empirical phenomenon increasingly exceeds what these models were built to explain. When AI becomes embodied (smart clothing) or embedded in public retail space (robots, in-store personalization systems), consumers confront not only convenience and novelty but also surveillance, boundary negotiation, and autonomy constraints [65,66].

Across studies, a familiar contradiction reappears: consumers value context-aware assistance and immersive experience, yet discomfort rises when systems are perceived as intrusive, opaque, or socially violating, e.g., [64]. This pattern is consistent with the broader cross-theme tension identified above: AI that “helps” can also “encroach.” Theoretical blind spots are again evident. The literature acknowledges the personalization–privacy trade-off, but it pays less attention to examining how consumers actively manage boundaries over time, adapt behavior in response to monitoring, or recalibrate acceptance as reliance grows. These omissions matter because embodied and in-store AI are precisely the contexts where autonomy and privacy costs can become most salient and where longitudinal dynamics are likely to shape outcomes.

Across themes, the GenAI-era fashion literature repeatedly circles the same conceptual knot: AI systems are designed to enhance consumer experience through human-likeness (anthropomorphism), meaning and legitimacy cues (authenticity), and decision support (autonomy-related delegation), yet these same features generate predictable forms of tension and resistance. The contradictions observed across streams suggest that the field’s next step is not simply to expand topical coverage, but to more directly theorize when and why anthropomorphism backfires, authenticity is destabilized, and autonomy becomes contested, especially as AI evolves from assistive tools to proactive, generative, and agentic participants in consumer life. From a TTM standpoint, the most pressing barrier to cumulative knowledge development is therefore not a lack of empirical effort, but a mismatch between rapidly evolving AI roles and theoretical models that remain optimized for early-stage adoption and short-term evaluation rather than ongoing negotiation of agency, legitimacy, and control in identity-relevant fashion contexts.

4. Future Research Agenda

4.1. Fashion-Specific Future Research Agenda

The rapid evolution of AI applications in fashion and e-commerce highlights the need for a focused research agenda that addresses key gaps in recent empirical consumer studies. Drawing on the thematic, theoretical, and methodological findings of this review, we propose a TTM-informed future research agenda organized around three interconnected dimensions (theme, theory, and method) and summarized in Table 6. Rather than offering a generic list of open questions, this agenda identifies theoretically motivated, high-potential research positions by systematically recombining themes, theories, and methods to advance conceptual development in AI-driven fashion research.

Table 6. Research agenda in the fashion domain.

TTM Framework	Future Research Directions	Rationales	Research Question Examples
Theme Perspective	Extend and deepen research on advanced, AI-driven, specific applications in fashion	- Existing research lags behind the rapid advancement of AI-related technologies applied in the fashion industry. - Research on general AI applications provides limited practical implications for fashion-specific contexts.	- How do consumers perceive, evaluate, and adopt GenAI-powered, image-based virtual try-ons? - How can GenAI-driven customization processes meet consumers' expectations? - Would consumers prefer or resist advanced multimodal AI-chatbots (integrating video, image, voice, and text), and why?
	Investigate cross-theme combinations and comparisons	- AI-driven applications often operate across multiple service contexts, reflecting real-world experiences. - A notable research gap exists in studies comparing and integrating cross-theme applications.	- How do consumers compare chatbot-based styling services with AI-powered human-like stylists? - How do consumers evaluate virtual wardrobe management systems when combined with GenAI-based virtual try-ons? - How do consumers perceive styling services that integrate wardrobe curation and new-item recommendations?
Theory Perspective	Context-dependent expansion of theoretical frameworks	Needs for theoretical lenses that align with the pace of AI advancements in fashion.	- Which theories from other disciplines (e.g., Computer Science, Information Systems) can be adapted to study AI-based fashion applications? - Is the emerging Digital Agenticity Theory (which explains users' psychological engagement with AI conversational agents) suitable for research on AI-powered fashion services?
	Apply multiple theoretical frameworks to specific consumer-facing scenarios	Enable a more holistic understanding of consumers' needs, motivations, and ethical considerations.	- How can researchers capture the psychological, relational, and ethical dynamics of human-AI interaction in AI-powered fashion services? - How can interdisciplinary theories be applied to better understand consumer behavior in AI-driven fashion contexts?
Method Perspective	Adopt mixed-method research designs	Combining quantitative and qualitative approaches enhances the depth, accuracy, and comprehensiveness of insights into consumer experiences.	- What are the key drivers and barriers influencing consumers' acceptance of AI human stylists, based on in-depth interviews? - Do factors identified from qualitative insights significantly predict consumers' acceptance of AI stylist recommendations?
	Conduct fashion-specific experimental research	Few experimental studies have focused directly on AI applications within the fashion industry.	Does the integration of GenAI-based, image-based virtual try-on application significantly influence consumers' adoption of virtual wardrobes?
	Employing diverse and advanced data analysis approaches	- Existing quantitative research often tests only linear relationships. - Broader analytical approaches can reveal deeper insights into complex consumer-AI interactions.	- How can machine learning techniques be applied to test non-linear relationships among factors influencing consumers' perceptions and engagement in AI-driven fashion applications? - How can segmentation analysis be applied to identify distinct consumer groups in such applications?

Theme-focused directions. Future research should move beyond broad treatments of “general AI” to examine specific, advanced applications in fashion. As the industry increasingly adopts GenAI-enabled image-based virtual try-ons, multimodal chatbots, and AI-powered new-item recommendations, empirical studies are needed to assess how consumers perceive, evaluate, and adopt these innovations. Particular attention should be paid

to mechanisms underlying trust, resistance, acceptance, and disclosure. Underexplored technologies, including multimodal generative styling systems, agentic shopping assistants spanning the purchase journey, affective AI with emotion recognition, and synthetic fashion influencers, raise novel issues related to experience, transparency, and governance that warrant targeted investigation. Comparative and integrative studies (e.g., AI chatbot stylists versus AI human stylists; hybrid systems combining wardrobe curation and recommendations) can further illuminate how consumers navigate multiple AI touchpoints within an integrated fashion ecosystem. Importantly, ethical, cultural, and regulatory considerations, such as bias, autonomy, and transparency, should be explicitly incorporated to enhance both theoretical and practical relevance.

Theory-focused directions. Although the literature shows substantial theoretical dispersion, this review does not advocate indiscriminate theory expansion. Instead, the TTM synthesis supports a selective, context-dependent strategy that differentiates between mature and emerging research streams. For established areas such as AI-powered chatbots and general AI services, progress will come from theoretical consolidation with targeted extension, moving beyond initial adoption to examine post-adoption dynamics (e.g., dependence, disengagement, trust calibration) using constructs related to autonomy, perceived AI capabilities, service benefits, and ethics within existing frameworks (e.g., MPT, UGT, ABC, BRT).

In contrast, less developed streams, including AI-driven recommendations, AI-assisted design, virtual influencers, and AI-generated marketing content, often involve experiences outside the scope of adoption-oriented models. Consumer responses to AI-designed fashion products, for instance, are frequently shaped by perceptions of authorship, creativity, and authenticity, while virtual influencers raise questions of social identity, persuasion legitimacy, and moral discomfort that are not adequately addressed by dominant technology acceptance and stimulus-response frameworks. In these contexts, introducing additional theories reflects conceptual necessity, not proliferation. For example, emerging perspectives such as Digital Agenticity Theory [69], which explains users' psychological engagement with AI conversational agents, offer promising foundations for examining communication-based fashion styling services. Furthermore, applying multiple lenses and interdisciplinary perspectives can further enrich the understanding of functional, emotional, social, and ethical dynamics.

Method-focused directions. Methodological advancement requires greater rigor and diversity. The field's reliance on cross-sectional, self-reported surveys limits causal inference and ecological validity. Future studies should incorporate longitudinal designs, behavioral experiments, field studies, and mixed-method approaches. Integrating qualitative methods (e.g., interviews, focus groups, ethnography) with quantitative analyses can capture both subjective experiences and observable behaviors. Fashion-specific experimental designs are particularly needed to establish causal effects of AI applications (e.g., testing how GenAI-based virtual try-ons influence trust and engagement in styling recommendations). Advanced analytical techniques, including supervised and unsupervised machine learning, can reveal non-linear effects, latent segments, and dynamic relationships, strengthening both methodological rigor and theoretical contribution.

Cross-contextual directions. Guided by the TTM framework, future research can develop stronger positioning through cross-contextual integration across the theme–theory–method, theme–theory, theory–method, and theme–method dimensions. Although the TTM-guided synthesis reveals numerous opportunities, several directions merit prioritization due to their theoretical centrality, empirical ambiguity, and managerial relevance. Advancing cumulative knowledge in the GenAI era requires deeper engagement with

emerging AI service paradigms that are reshaping consumer decision-making, identity construction, and human–AI interaction.

First, AI-driven styling services, particularly new item recommendation and wardrobe management systems, represent a critical priority. These services increasingly operate as longitudinal, data-intensive, and adaptive decision partners rather than episodic advisory tools. Future research could extend Digital Agenticity Theory [69] by examining how conversational AI capabilities shape evolving perceptions of competence, personalization, and trust within sustained styling relationships. Integrating Privacy Calculus Theory can further clarify how consumers negotiate the perceived benefits of AI competence against privacy concerns associated with intimate data disclosure, including visual, biometric, and behavioral inputs. Methodologically, this domain would benefit from mixed-method designs that combine qualitative interviews capturing consumer meaning-making and identity dynamics with large-scale online surveys testing linear and nonlinear relational mechanisms.

Second, comparative research on human-like AI stylists versus chatbot-based stylists constitutes a high-impact direction. As AI interfaces become increasingly human-like, research must move beyond static assessments of anthropomorphism to examine the psychological mechanisms underlying acceptance and resistance. Extending Uncanny Valley Theory, e.g., [70,71], future studies should investigate how varying degrees of human realism influence discomfort, perceived sophistication, competence, and disclosure willingness. Evidence indicating that uncanniness may produce both negative and positive downstream effects highlights the need for theoretical refinement, particularly regarding non-linear and competitive mediation processes [72]. Empirically, interview-based exploration can uncover nuanced interpretive and emotional responses, while controlled online experiments can isolate causal effects of interface realism, proactivity, and disclosure transparency.

Third, AI agent-powered fashion shopping services represent a strategically important frontier [7]. Unlike traditional assistive tools, agentic systems proactively curate, recommend, and potentially act on consumers' behalf. This shift challenges prevailing adoption frameworks by foregrounding issues of delegated agency, autonomy negotiation, reliance, and trust calibration. Future research could further develop Digital Agenticity Theory by distinguishing between perceived agentic capability and perceived autonomy threat. Incorporating perspectives from consumer future-oriented decision-making literature, such as the Spiral of Silence Theory, may offer additional insight into how consumers interpret the anticipated normalization of agentic commerce [73]. Methodologically, this stream would benefit from behavioral simulations, online surveys, and scenario-based experiments capable of capturing dynamic adaptation and reliance formation.

Collectively, these prioritized directions address central contradictions identified in the TTM synthesis, particularly those related to competence, human-likeness, privacy, authenticity, and autonomy. More broadly, they shift the research agenda beyond incremental extensions of technology acceptance toward deeper theoretical engagement with the agentic, generative, and relational nature of contemporary AI systems in fashion contexts. Overall, this agenda positions AI-related consumer research in fashion as a dynamic field poised for transformative growth, offering pathways to sustainable, ethical, and consumer-empowering innovation with clear relevance for scholars and practitioners alike.

4.2. Broader Implications for E-Commerce Scholarship and Practice

The proposed future research agenda has implications that extend beyond the fashion sector, offering pathways for advancing e-commerce scholarship and practice in the GenAI era. By extending the TTM framework beyond fashion-specific contexts, this section

outlines how insights from AI-driven fashion research can inform the design, governance, and methodological advancement of next-generation e-commerce ecosystems.

Thematic implications. Examining both specialized AI applications and cross-theme integrations is critical for building sustainable and competitive e-commerce systems. For example, insights from GenAI-powered image-based virtual try-ons in fashion can inform adaptive preview technologies in categories such as furniture or electronics, potentially reducing return rates and decision fatigue. Similarly, hybrid AI systems that integrate styling, recommendation, and decision support in fashion anticipate broader forms of ecosystem orchestration, in which AI enables seamless consumer journeys from discovery to fulfillment. Developing measures of AI touchpoint fluidity, capturing how consumers navigate multi-stage digital pathways, can guide platform design toward low-effort, high-trust experiences. In practice, these insights support modular AI toolkits that lower barriers to personalization and enable small and medium-sized enterprises to compete in data-intensive markets.

As AI-driven personalization becomes pervasive, ethical and emotional considerations become increasingly central. Addressing privacy, transparency, and algorithmic bias is essential for sustaining consumer trust. Future research should examine how explainability mechanisms shape confidence, loyalty, and long-term engagement, informing responsible AI governance. Insights from fashion, where identity, aesthetics, and self-expression are salient, also provide a valuable foundation for designing emotionally responsive e-commerce systems. Multimodal GenAI interfaces that integrate text, image, and voice may foster empathy and continuity in online retail, warranting further investigation into their effects on satisfaction, conversion, and customer equity across sectors.

Theoretical implications. The findings point to the need for convergent e-commerce theories that integrate domain-specific insights with broader principles of digital trust, autonomy, and agency. Extending perspectives such as Digital Agency Theory beyond fashion can reframe AI as an active co-creator in value exchange rather than a purely functional tool. Applying multiple theoretical lenses can further clarify how constructs such as anthropomorphism, autonomy, and trust vary across contexts, helping scholars explain consumer resistance and adaptation to AI-driven systems. For practitioners, such theorization supports proactive design and auditing of AI systems to strengthen relational trust and brand resilience.

Methodological implications. Methodological advancement in e-commerce research requires integrating mixed-method designs with computational analytics. Combining behavioral experiments with machine learning enables the identification of non-linear and dynamic relationships between consumer perceptions and AI engagement. Future studies leveraging real-time platform data can model adaptive feedback loops between consumers and AI systems, offering scalable and contextually grounded insights. For practitioners, these approaches enhance data-driven decision-making in personalization, segmentation, and strategic forecasting.

Overall, the TTM-guided agenda provides a blueprint for strengthening the theory–practice nexus in e-commerce research. By systematically linking themes, theories, and methods, future studies can generate actionable insights for platform design, consumer engagement, and strategic innovation, while reinforcing ethical, consumer-centric principles across evolving digital marketplaces.

5. Conclusions and Limitations

This study provides a systematic and bibliometric synthesis of empirical research on AI-driven consumer behavior in the fashion industry (2022–2025), guided by the Theme–Theory–Method (TTM) framework. The review maps the current research landscape

by identifying dominant themes, theoretical foundations, and methodological patterns. Thematic analysis shows that AI-powered chatbots and general AI services in fashion receive the greatest scholarly attention, followed by AI-driven recommendations, AI-assisted product design, virtual influencers, in-store AI applications, smart clothing, and AI-generated marketing content. Theory-driven analysis identifies 22 theoretical frameworks, with the Technology Acceptance Model (TAM) and Stimulus–Organism–Response (SOR) framework most frequently applied. Methodologically, the literature is dominated by quantitative designs, although mixed-method and qualitative approaches are increasingly used to capture more nuanced consumer experiences.

Building on these findings, the study proposes a TTM-informed future research agenda that addresses key gaps and provides structured directions for theory development and empirical inquiry. By consolidating fragmented evidence, integrating thematic and bibliometric insights, and identifying areas of misalignment across themes, theories, and methods, the review enhances understanding of how AI is reshaping consumer behavior in fashion. Beyond its sectoral focus, the study offers broader implications for e-commerce scholarship and practice, demonstrating how insights from fashion, an industry at the forefront of digital innovation, can inform responsible and human-centered AI applications across online retail contexts.

The review also generates several forms of conceptual clarity absent from prior work. First, the TTM framework reveals systematic imbalances across research themes, theoretical lenses, and methods, offering direct guidance for future studies. Second, triangulation of thematic and bibliometric analyses uncovers a shift from predominantly functional, adoption-oriented research toward experiential, social, and agentic perspectives on AI-mediated consumption. Third, the findings highlight a growing misalignment between rapidly diversifying AI applications and the explanatory capacity of existing frameworks. Fourth, the analysis demonstrates the coexistence of theoretical consolidation and dispersion across research streams, reflecting uneven field maturity. Finally, it shows that methodological homogeneity, particularly the dominance of online survey designs, limits causal inference and constrains understanding of dynamic human–AI interactions.

Several limitations should be noted. The review focuses on empirical studies published between 2022 and 2025, which may exclude earlier conceptual contributions and longer-term developments. In addition, reliance on specific databases and search criteria may have resulted in the omission of relevant studies indexed elsewhere or using alternative terminology. Finally, limiting the corpus to peer-reviewed journal articles excludes industry reports and practitioner-oriented case studies that could offer complementary insights.

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with PRISMA 2020 Item 27, full files will not be made publicly available. Only aggregated results (e.g., Tables 2–5 and Figures 2 and 3) will be presented in the manuscript's Findings section.

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