International Journal of Trend in Scientific Research and Development (IJTSRD)
Special Issue on Smart Innovations in Computer Science and Applications
Available Online: www.ijtsrd.com e-ISSN: 2456 – 6470

Design of a Smart Fashion Shopping Platform with AI Recommendations and Real-Time Price Aggregation

Namita Raghuwanshi
Department of Master of Computer Applications,
G. H. Raisoni Skill Tech University, Nagpur, India

Annotation

The way people shop for fashion online has shifted quite dramatically over the last few years. Consumers today no longer simply look for clothes — they want the right clothes, at the right price, from the right platform, all without switching between multiple apps. Yet, when one looks at the landscape of existing fashion e-commerce platforms, a rather glaring problem becomes visible: personalization, price discovery, and user experience are each handled in isolation, never together. In this paper, we take up exactly this challenge and propose a unified platform architecture that brings all three dimensions under one roof.

In this research, the proposed system integrates an AI-based recommendation engine built on CLIP embeddings and ResNet50-based collaborative filtering, a real-time multi-vendor price aggregation module powered by web scraping and RESTful microservices, and an adaptive UI/UX layer designed around user-centered principles. The platform targets fashion-conscious digital consumers who demand both personalization and value transparency. In this paper, we draw upon thirteen existing peer-reviewed research works to map the current state of the field, analyze their individual strengths and weaknesses, and identify the precise gap that this research occupies.

The findings of this research suggest that fusing these three sub-systems within a single scalable platform represents a novel and practically significant contribution to fashion e-commerce. In this paper, no prior work was found that addresses all three dimensions simultaneously, which establishes the originality of this research.

Keywords: Fashion E-Commerce, Personalized Recommendation System, Real-Time Price Aggregation, Adaptive UI/UX Design, Deep Learning, Collaborative Filtering, CLIP Model, Web Scraping, Multi-Vendor Platform, Next-Generation Shopping Platform.

1. INTRODUCTION

Online fashion retail is no longer just a convenience — for a large and growing number of consumers, it is the primary mode of shopping. The global fashion e-commerce market was valued at $888.56 billion in 2024 and is expected to cross $974 billion by 2025, growing at a compound annual rate of 9.7% [1]. Numbers like these speak to an industry that is both massive and fast-moving. But beneath this growth lies a problem the industry has not yet solved: the consumer experience remains fragmented.

In this research paper, I read and understand that a typical fashion shopper today will open one app for recommendations, another to compare prices, and yet another for a better interface — and still might not find what they need. In this paper, we argue that this fragmentation is not a minor inconvenience; it is a structural failure of current platform design. Existing systems are built around one of three pillars [2, 3, 4]: they are either good at recommending products based on taste, or good at aggregating deals across vendors, or good at providing a clean user interface. Very rarely are they even two of these three, and none of the works reviewed in this research achieves all three simultaneously.

In this research paper, I read and understand from the literature that fashion as a domain carries unique challenges not found in other product categories [5]. A recommendation engine that works for electronics cannot simply be transplanted into a fashion platform — compatibility between items, visual aesthetics, seasonal relevance, and rapidly shifting trends all need to be accounted for. Similarly, price aggregation in fashion is complicated by the large number of vendors, frequent discount cycles, and the fact that the same product may be listed under different names across platforms [6, 7].

In this paper, we address all of these dimensions through a single unified architecture. The contributions of this research are: first, an integrated system combining AI-powered recommendations, live multi-vendor price aggregation, and adaptive UI/UX; second, a structured literature review that systematically identifies gaps in existing work; and third, a platform design validated through architecture modeling and comparative analysis [8, 9].

Fig. 1 below provides the high-level architectural view of the proposed system. The platform is divided into a User Layer (the adaptive interface), an AI Engine Layer (the recommendation and deal-scoring engine), and a Data Layer (multi-vendor aggregation and user profile management).

Fig. 1 — High-Level Architecture of the Proposed Unified Fashion Platform

USER LAYER	AI ENGINE LAYER	DATA LAYER
Adaptive Web/Mobile UI Responsive Design User Preference Profiles	CLIP + ResNet50 Model Collaborative Filtering Deal Scoring Engine	Multi-Vendor Scraper RESTful API Gateway SQL + NoSQL Database
Backend Microservices Architecture — Unified API Gateway — Cloud Deployment		

2. LITERATURE REVIEW

What follows is an analysis of thirteen research papers reviewed as part of this research. Each paper was selected based on relevance to one or more of the three core pillars of the proposed platform: AI-driven fashion recommendations, price aggregation and deal discovery, and UI/UX design for fashion e-commerce systems. The sources include ScienceDirect, Google Scholar, Springer Nature, IEEE Xplore, ResearchGate, PubMed Central, and IJRTI.

A. AI-Based Fashion Recommendation Systems

[1] Mulewar et al. (2026) — Development of AI Based Fashion Recommender System for E-commerce Business, Springer SmartCom 2025.

This paper introduces a fashion recommendation method that uses ResNet50 pre-trained CNN to extract visual features from single product images and pairs them with collaborative filtering to generate personalized suggestions. The authors also discuss VITON — a virtual try-on network that overlays clothing onto user images using a coarse-to-fine generation strategy. In this research, I read this paper to understand how visual feature extraction forms the backbone of product matching in an e-commerce environment.

Useful Content: Visual similarity via ResNet50; collaborative filtering for personalization; VITON for virtual try-on.

Pros: Strong product matching accuracy; virtual try-on improves user engagement; ResNet50 outperforms other CNNs.

Cons & Gap: No price transparency; no multi-vendor support; cold-start problem unaddressed; UX design not evaluated. This research moves beyond by integrating pricing and adaptive UX alongside AI recommendations.

[2] Banerjee et al. (2025) — Agentic Personalized Fashion Recommendation in the Age of Generative AI, ACM SIGIR 2025.

This perspective paper lays out how large vision-language models and agentic LLMs can power the next generation of fashion recommenders. The authors introduce multimodal grounding — where text requests like 'formal, under Rs. 2000' are fused with image inputs — and demonstrate how real-time embedding synthesis alleviates cold-start issues. In this paper, I understand the value of generative AI in building context-aware fashion recommendation pipelines.

Useful Content: Multimodal grounding; agentic LLM framework; dialog-based recommendations; cold-start mitigation.

Pros: Handles rapid trend changes; builds trust via dialogue; reduces return rates.

Cons & Gap: Heavy compute requirements; no deal or pricing awareness; no UX evaluation included. This research draws on multimodal concepts but incorporates them into a lighter, deal-aware system.

[3] Choi et al. (2024) — Dress-UP: A Deep Unique Personalized Fashion Recommender, Stanford CS231N.

The authors investigate using CLIP and FashionCLIP for zero-shot and few-shot fashion recommendation — generating personalized outfit suggestions from minimal user context to avoid the large behavioral dataset dependency that traditional recommenders carry. In this research, I read this paper to understand how CLIP embeddings can serve as an efficient foundation for the AI engine of the proposed platform.

Useful Content: CLIP-based embeddings for image-text fashion matching; privacy-preserving personalization without requiring extensive behavioral data.

Pros: Works with limited user data; open-source model base; strong zero-shot generalization.

Cons & Gap: Not deployed on a live platform; no e-commerce or pricing integration. In this research, we build upon CLIP within a fully integrated e-commerce context.

[4] Shirkhani & Mokayed (2023) — Study of AI-Driven Fashion Recommender Systems, SN Computer Science, Springer Nature.

A comprehensive literature review spanning AI techniques in fashion recommendation over ten years, this paper establishes that compatibility — not just similarity — is the core challenge in fashion recommendation. Unlike movie or electronics recommenders, fashion systems must evaluate how well two items work together visually and contextually. In this paper, I use this work as the theoretical anchor for understanding the uniqueness of fashion as a recommendation domain.

Useful Content: Compatibility versus similarity distinction in fashion; image-based recommender taxonomy; overview of deep learning techniques.

Pros: Thorough theoretical base; well-organized taxonomy; covers a decade of research.

Cons & Gap: No implementation; no pricing or UX coverage. This research implements a system that addresses the compatibility challenge within a deal-aware platform.

[5] Kumar et al. (2025) — AI-Powered Fashion Outfit Recommender, IJRTI Vol. 10, Issue 5.

This paper presents a working system using CLIP for wardrobe management — users upload images of their clothing, which the system processes to recommend outfits, and when an item is missing, suggests purchase alternatives from platforms like Amazon and Flipkart. The backend uses

Express.js and Flask. In this research, I understand from this paper that e-commerce integration with AI recommendation engines is technically feasible and practically valuable.

Useful Content: CLIP wardrobe analysis; Express.js and Flask backend; e-commerce link integration for missing items.

Pros: Working deployed system; integrates e-commerce links; context-aware outfit suggestions.

Cons & Gap: No live price comparison across vendors; privacy concerns with wardrobe uploads; no adaptive UI layer. This research improves by adding real-time multi-vendor pricing and a responsive design component.

C. UI/UX Design for Fashion E-Commerce

[1] Chakraborty et al. (2026) — From Reviews to Results: A Mixed-Methods Evaluation to Understand UX in Fashion Apps, ScienceDirect.

This study applies the SERVQUAL framework to evaluate user experience on major Indian fashion apps — Ajio, Myntra, and Snapdeal. The research finds that service quality, emotional connection, and perceived care significantly shape UX in fashion apps — going well beyond simple interface usability. Delivery reliability and return processes emerged as major UX drivers. In this research, I use this paper to anchor the UX evaluation criteria for the proposed platform.

Useful Content: SERVQUAL-based UX assessment; emotional UX factors in fashion; service quality dimensions for app evaluation.

Pros: Indian market focus (highly relevant to the target user base); strong mixed-method design; covers emotional and functional UX dimensions.

Cons & Gap: No AI integration; no pricing features evaluated; only analyzes existing apps without proposing a new design. This research proposes a new UX framework informed by these findings.

[2] Karim et al. (2024) — UI/UX Design Impact on E-Commerce Attracting Users, ScienceDirect / Procedia Computer Science.

This paper examines the direct relationship between UI/UX quality and user acquisition in e-commerce platforms. It argues that in the digital era, e-commerce platforms function as transactional bridges between users and sellers, and that the quality of these bridges has a measurable impact on whether users stay or leave. Poor UI/UX, the paper demonstrates, directly drives cart abandonment and reduces conversion rates. In this research, I read this paper to understand why UI/UX is not cosmetic — it is structural to platform success.

Useful Content: UI/UX as driver of conversion; relationship between design quality and user retention; digital touchpoint design principles.

Pros: Strong empirical grounding; directly applicable to e-commerce platform design; published in ScienceDirect.

Cons & Gap: Not fashion-specific; no AI or pricing consideration; no mobile-first design discussed. This research builds a fashion-specific adaptive UI informed by these findings.

[3] Roy et al. (2025) — Understanding User Experience for Mobile Applications: A Systematic Literature Review, Springer Discover Applied Sciences.

This systematic review of 205 documents on mobile app UX establishes the STFM framework (Scenarios, Themes, Features, and Methodologies) for evaluating UX across mobile contexts. It highlights that shopping is one of the dominant scenarios where personalized UX significantly affects user satisfaction. Interface elements, interaction styles, and performance enhancements are identified as the three most critical design levers. In this paper, I understand from this work how to structure UX evaluation for a mobile-first fashion platform.

Useful Content: STFM UX framework; personalization as UX driver; shopping-context UX design principles; interaction style impact.

Pros: Comprehensive scope reviewing 205 documents; practical STFM framework; directly applicable to mobile app design.

Cons & Gap: Not fashion-specific; no pricing or AI discussed; framework remains theoretical. This research applies STFM principles within a concrete fashion e-commerce system.

[4] Ghosh et al. (2025) — Innovations in UI/UX Design of Mobile Applications: Trends, Practices and Challenges, ResearchGate.

This paper reviews innovation trends in mobile UI/UX design drawing from ScienceDirect, SpringerLink, and IEEE Digital Library. It identifies AI-integrated design thinking, adaptive interfaces, and continuous feedback loops as the most impactful trends shaping mobile UX in 2024-2025. The paper also acknowledges the tension between device hardware constraints and growing user expectations. In this research, I read this paper to understand the current frontier of UI/UX innovation relevant to the proposed platform.

Useful Content: AI-driven design thinking; adaptive interface principles; continuous feedback-loop based UX improvement; constraint-aware design guidance.

Pros: Covers 2024-2025 trends; wide source base including ScienceDirect and IEEE; practical design guidance.

Cons & Gap: General mobile apps — not fashion-specific; no pricing or recommendation integration. This research applies adaptive interface design within a specialized fashion platform.

Table 1 — Comparative Summary of Reviewed Research Papers

Ref.	Authors (Year)	Focus Area	Key Contribution	Gap Identified	Relevance
[1]	Mulewar et al. (2026)	AI Recommendation	ResNet50 + VITON fashion rec.	No pricing; no UX	AI engine design
[2]	Banerjee et al. (2025)	Generative AI Rec.	Agentic LLMs + VLMs	No deal awareness	Multimodal rec. base
[3]	Choi et al. (2024)	CLIP Recommendation	CLIP outfit rec. zero-shot	No e-commerce deploy	CLIP as AI base model
[4]	Shirkhani et al. (2023)	AI Survey (Fashion)	Fashion rec. taxonomy	No implementation	Theoretical grounding
[5]	Kumar et al. (2025)	AI + E-Commerce	CLIP wardrobe + buy links	No price comparison	System arch. reference
[6]	Patil et al. (2024)	Hybrid Recommendation	Multi-label hybrid rec.	No pricing / UX layer	Hybrid AI design pattern
[7]	Pranav et al. (2025)	Price Comparison	Web scraping + alerts	Not fashion-specific	Scraping architecture
[8]	Bramesh et al. (2025)	Price Aggregation	Scalable multi-vendor arch.	No fashion / AI / UX	Aggregation module ref.
[9]	Almahadeen et al. (2025)	Dynamic Pricing	Sentiment-ML pricing model	No consumer-facing UI	Pricing intelligence
[10]	Chakraborty et al. (2026)	Fashion App UX	SERVQUAL fashion UX eval.	No AI / pricing eval.	UX evaluation criteria
[11]	Karim et al. (2024)	UI/UX E-Commerce	UI/UX vs. conversion link	Not fashion-specific	UX design rationale
[12]	Roy et al. (2025)	Mobile UX Review	STFM UX framework	No fashion / AI scope	Mobile UX framework

[13]	Ghosh et al. (2025)	UI/UX Innovations	Adaptive interface trends	No fashion / pricing	Adaptive UI principles

3. RESEARCH GAP AND PROBLEM STATEMENT

After reviewing the thirteen papers above, the research gap becomes apparent and is worth stating clearly. Every paper reviewed in this research addresses, at most, one or two of the three core challenges. Papers [1] through [6] deal with AI-based fashion recommendation — but none of them incorporate real-time pricing or multi-vendor deal discovery. Papers [7] through [9] address price aggregation and dynamic pricing — but they do not consider fashion-specific personalization or user experience. Papers [10] through [13] focus on UI/UX design — but they evaluate existing apps or propose theoretical frameworks, none proposing a new system that combines UX with AI and pricing.

In this research, the core problem being solved is: how can a single platform simultaneously serve a fashion consumer's need for style personalization, price transparency across vendors, and a seamless, adaptive browsing experience? Current platforms fail this test. Myntra and Ajio offer good UX but poor price transparency. Google Shopping offers price comparison but no fashion intelligence. Generic recommendation engines do not understand fashion compatibility. None of these systems solve all three problems as a unified whole [10, 11, 12].

The research gap, therefore, is the absence of an integrated, fashion-specific platform that unifies: (i) AI-powered multimodal recommendations accounting for compatibility and trends, (ii) real-time aggregation of product prices and deals from multiple vendors, and (iii) an adaptive UI/UX framework shaped around the emotional and functional expectations of fashion consumers. In this research, we fill that gap.

4. PROPOSED SYSTEM ARCHITECTURE

The proposed platform is structured around three tightly coupled modules that communicate through a shared API gateway and a unified data store. Rather than treating recommendation, pricing, and interface as separate concerns, the architecture is designed so that each module can inform the others. The price aggregation module, for instance, feeds discount signals into the recommendation engine, which then prioritizes deals on items a user is likely to enjoy anyway.

A. AI Recommendation Engine

The recommendation module uses a dual-model approach. For visual similarity and compatibility, the system uses CLIP embeddings to match product images with user preferences expressed as text or prior interaction history [3, 5]. For collaborative filtering — recommending items based on what similar users have purchased — the system uses ResNet50 to extract deep visual features from product images, feeding them into a k-nearest-neighbor matching model [1, 6]. This dual approach addresses cold-start users via CLIP's zero-shot capability and returning users via ResNet50-based collaborative filtering.

B. Real-Time Price Aggregation Module

The price aggregation layer pulls product pricing data from multiple e-commerce vendors using a combination of publicly available APIs and web scraping with BeautifulSoup and Selenium, mirroring the approach described in [7, 8]. Products are matched across vendors using normalized identifiers and name-similarity algorithms. The module maintains a pricing database updated at regular intervals and stores historical trends to support price-drop alerts. Results are scored using a deal-ranking algorithm that weighs price, discount percentage, vendor reliability, and delivery time [9].

C. Adaptive UI/UX Layer

The interface layer is built on user-centered design principles from the literature [10, 11, 12, 13]. The UI is responsive across desktop and mobile, and dynamically adapts its layout based on the user's browsing behavior — surfacing deals when the user shows price-sensitivity, or surfacing style-matched recommendations when the user is in an exploratory browsing mode. The UX framework applies the SERVQUAL dimensions from [10] to ensure that functional usability, emotional engagement, and trust are all addressed in the design.

5. METHODOLOGY

In this research, the methodology follows a design science approach — the objective is to design, describe, and validate a novel system artifact. This research does not conduct a live user study or deploy the system to production; rather, it proposes the architecture, validates it through literature-backed design decisions, and demonstrates its novelty through a comparative gap analysis.

The AI recommendation module was designed through a review of models documented in [1], [2], [3], and [6], and the choice of CLIP combined with ResNet50 was made based on their documented performance in fashion-specific contexts. The price aggregation module was designed based on the architectural patterns described in [7] and [8], adapted for the fashion domain. The UI/UX framework was developed from the evaluation criteria documented in [10], [11], [12], and [13].

The integration of the three modules was validated architecturally by checking that data flows between them are consistent — specifically, that the output schema of the recommendation engine and price aggregation module can both be rendered by the UI layer without data transformation bottlenecks. A system-level data flow was traced from user query to final recommendation display with price context.

6. RESULTS AND DISCUSSION

The primary result of this research is the architecture specification of a unified fashion deals and shopping platform. The comparative analysis of the thirteen reviewed papers confirms that this architecture occupies a space that no prior research has addressed. Table 1 makes this visible: while every paper contributes something useful to one of the three pillars, none bridges all three.

The design decisions made in this research are supported by specific prior works. The choice of CLIP for zero-shot fashion understanding is validated by [3], where CLIP outperformed traditional models on fashion retrieval tasks without requiring behavioral training data. The ResNet50-based collaborative filtering component is supported by [1], which empirically demonstrated ResNet50's superiority over other CNNs for fashion recommendation. The web scraping and API-based aggregation approach is directly informed by [7] and [8], which showed its feasibility and accuracy in comparable e-commerce settings.

From a UX standpoint, the adaptive interface design draws from [10], [11], and [12], which collectively establish that fashion app users respond strongly to emotional design cues, personalization, and trust signals. The finding from [10] — that Indian fashion app users on Myntra and Ajio are frequently dissatisfied with return process clarity and service responsiveness — directly informed the UX design principles of the proposed platform, particularly the emphasis on transparent deal presentation and clear vendor information.

One discussion point worth noting is the engineering challenge of synchronizing the three modules. Real-time price aggregation introduces latency that could affect recommendation display. In this research, we propose solving this through asynchronous loading — the UI first renders AI recommendations from cached data, while the price aggregation data loads in the background and updates the display without a full page reload, consistent with Progressive Web App (PWA) design patterns.

7. CONCLUSION AND FUTURE WORK

In this paper, we proposed and described a next-generation unified fashion deals and shopping experience platform that integrates AI-powered personalized recommendations, real-time multi-vendor price aggregation, and adaptive UI/UX design within a single coherent system. The literature review of thirteen papers confirmed that this combination has not been previously achieved, establishing the novelty of this research.

The proposed architecture — built around CLIP and ResNet50 for recommendations, web scraping and RESTful APIs for price aggregation, and user-centered adaptive design for the interface — is grounded in well-validated prior work and addresses the specific gaps identified in each reviewed paper. The system is designed to serve fashion consumers who demand both personalization and price transparency.

Future work in this research area should include: (i) a live deployment with a real user base to gather behavioral data and UX feedback; (ii) incorporation of augmented reality try-on features as an extension of the recommendation layer; (iii) exploration of federated learning approaches that allow the AI engine to improve from user interactions without compromising privacy; and (iv) extension of the price aggregation module to support international vendors and currency normalization for cross-border fashion shopping.

REFERENCES

1. S. Mulewar, A. Patil, G. Patil, N. Chame, and S. Kulkarni, "Development of AI Based Fashion Recommender System for E-commerce Business," in Smart Trends in Computing and Communications, SmartCom 2025, Lecture Notes in Networks and Systems, vol. 1461, Springer, Singapore, 2026. https://doi.org/10.1007/978-981-96-7508-1_32
2. A. Banerjee, A. Satish, F. N. Aisyah, W. Wörndl, and Y. Deldjoo, "Agentic Personalized Fashion Recommendation in the Age of Generative AI: Challenges, Opportunities, and Evaluation," in Proc. ACM SIGIR 2025, Padua, Italy, July 2025. arXiv:2508.02342
3. E. Choi, "Dress-UP: A Deep Unique Personalized Fashion Recommender," Stanford CS231N Course Paper, 2024. Available: https://cs231n.stanford.edu/2024/papers/dress-up-a-deep-unique-personalized-fashion-recommender.pdf
4. H. Shirkhani and H. Mokayed, "Study of AI-Driven Fashion Recommender Systems," SN Computer Science, Springer Nature, 2023. https://doi.org/10.1007/s42979-023-01932-9
5. H. Kumar et al., "AI-Powered Fashion Outfit Recommender," International Journal for Research Trends and Innovation (IJRTI), vol. 10, no. 5, May 2025. ISSN: 2456-3315
6. A. Patil et al., "A Personalized Product Recommendation System for E-Commerce Platforms Based on Artificial Intelligence and Image Processing Technologies," Traitement du Signal, IIETA, 2024. https://doi.org/10.18280/ts.410615
7. H. Pranav, M. S. Harshini, T. Rachuri, and D. Radha, "E-Commerce Price Comparison Website Using Web Scraping," ResearchGate, February 2025.
8. B. S. Bramesh, D. Mahadeva, S. Shamitha, and P. Poorvik, "A Scalable Architecture for Real-Time Multi-Vendor Price Aggregation and Comparison," IJRASET, 2025.
9. L. Almahadeen, M. K. Rathod, S. F. Sulaiman, K. Deepika, G. R. Teltumbade, and R. Saravanakumar, "A Hybrid Sentiment-Aware Machine Learning Framework for Real-Time Dynamic Pricing in E-Commerce," IJIDML, 2025.
10. A. Chakraborty et al., "From Reviews to Results: A Mixed-Methods Evaluation to Understand UX in Fashion Apps," Technological Forecasting and Social Change, ScienceDirect, Elsevier, 2026.
11. M. Karim et al., "UI/UX Design Impact on E-Commerce Attracting Users," Procedia Computer Science, ScienceDirect, Elsevier, November 2024. https://doi.org/10.1016/j.procs.2024.031442