Revolutionizing Fashion through Personalized Shopping

AI-driven Recommendation Application

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Declaration

I hereby certify that this report constitutes my own work, that where the language of others is used, quotation marks so indicate, and that appropriate credit is given where I have used the language, ideas, expressions, or writings of others.

I declare that this report describes the original work that has not been previously presented for the award of any other degree of any other institution.

Uchechukwu G Aninta

Date: 13/05/2025

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Abstract

This dissertation describes the development and design of an artificial intelligence-based fashion recommendation system with a view to personalized shopping experiences in line with users' preferences and natural language input. The research tackles fundamental shortcomings in existing recommendation systems, such as the cold start problem, low adaptability to ambiguous queries, and poor support for sustainability and filtering by body type.

The review of recent literature established the performance of hybrid AI models, how deep learning and NLP contributed to enhancing personalization accuracy, and upcoming ethical issues concerning bias, privacy, and inclusiveness. These insights informed the development of a lightweight system using Django Rest Framework, Bootstrap, and SQLite, optimized for modularity and real-time performance.

The system's core innovation is its integration with Meta Llama 3.1 405B, a state-of-the-art large language model, which parses unstructured user prompts (e.g., "affordable wedding outfit for petite frame") into structured JSON filters. These filters are applied to a curated fashion item database via Django's ORM to generate context-aware recommendations. Profile-driven logic also supports returning users with enhanced personalization.

Empirical testing showed a significant improvement in recommendation relevance for first-time users and significantly better performance in interpreting ambiguous queries compared to rule-based methods. The system also supports eco-friendly and inclusive recommendations based on user-stated values and body types.

This work demonstrates that combining content-based filtering with LLM-driven contextual analysis can overcome cold start limitations and offer ethically aware, personalized fashion recommendations—setting a foundation for scalable, responsible AI in e-commerce.

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1. Introduction

The rise of AI-driven recommendation systems has transformed fashion e-commerce by offering personalized shopping experiences that cater to individual user preferences. Traditional systems rely on rule-based filtering, which generally cannot provide accurate and dynamic suggestions. This research aims to develop an artificial intelligence-driven recommendation system that integrates content-based filtering with large language model (LLM)-based artificial intelligence filtering to provide more precise, real-time suggestions. Unlike existing models that rely on big data and a lot of processing power, the research focuses on a lightweight, fast system that operates efficiently with small data sets, presenting users with relevant fashion choices based on their descriptions.
For example, if a consumer enters a "casual weekend brunch look for under $50," the system will read the key characteristics—occasion, budget, and style—then recommend a Green Maxi Dress ($20) or a Shirred Waist Hoodie ($25). The system infrastructure is a Bootstrap-driven front-end, Django Rest Framework backend, and MySQL database, with responsive and seamless interactions. Using Meta Llama 3.1 405B, the study looks to offer a seamless, AI-based shopping experience that streamlines search and improves the accuracy and relevance of the recommended fashion items, making shopping faster, more intuitive, and personalized.

Problem Description, Context and Motivation

Current recommendation systems in the fashion industry often require large-scale datasets and high computational power, making them inefficient for smaller-scale, personalized applications. These systems do not always provide highly personalized and context-specific recommendations, especially in low-data situations.

This study will develop an AI-driven recommendation system that bridges the gap by integrating Meta Llama 3.1 405B-based language processing with content-based filtering mechanisms. The proposed solution will provide accurate and user-specific fashion recommendations even with sparse data, with enhanced user interaction through real-time adaptability and interactive filtering mechanisms. This study will determine how the proposed method will increase shopping effectiveness, user satisfaction, and recommendation accuracy with a practical alternative to traditional large-scale recommendation systems.

Aims

The project aims to:

- Develop a hybrid AI recommendation system for fashion e-commerce.
- Improve personalization and relevance of recommendations using natural language inputs.
- Enhance accessibility through body-type and sustainability-aware suggestions.

Objectives

To achieve these aims, the project will:

- Implement a front-end interface using Bootstrap for real-time interaction.
- Design a backend with Django Rest Framework and SQLite for data processing and retrieval.
- Integrate Meta Llama 3.1 for natural language parsing and contextual filtering.
- Evaluate system performance against key metrics such as accuracy, speed, and personalization effectiveness

Research Questions

The study will aim to answer the following questions:

- How can AI-based filtering and content-based filtering be integrated to enhance personalization and recommendation accuracy for fashion shoppers?
- What benefits will AI-driven recommendation models provide over conventional rule-based filtering methods in terms of real-time interaction and versatility?
- To what extent will the system be able to deliver highly relevant and accurate recommendations based on user input, preferences, and inferred attributes?

Legal

The Project is regulated by legal, social, professional, and ethical standards to achieve its objective effectively and responsibly.

Legal considerations cover adhering to data protection regulations such as the General Data Protection Regulation (GDPR). Privacy of users' data is not a problem, as preference-based suggestions are based on capturing anonymized and safely stored information. Consent is gathered to utilize this information.

Social

Social factors seek to engage everyone in the process of suggesting fashion. The system needs to support the users' various needs by supporting various styles, sizes, and cultural considerations. Thus, the platform can support multiple users and provide an opportunity for various groups of people to access the process of recommending fashion.

Ethical

Ethical issues are also important considerations in the project, including the mechanisms to avoid bias in the suggested style. This way, the algorithms do not favor any particular fashion style, and the data set is not skewed with prejudices or highlights certain trends.

Professional

Professionalism is achieved through compliance with best practices in software development and deployment. The system is a user interface that is thoroughly tested and secure to give the user a smooth and reliable experience. These principles help maintain the project's integrity and are the key to its success.

Background

Recommendation systems are among the most effective tools that enhance user experience and participation across various domains by suggesting items or content based on users' previous interactions. Recommendation systems are classified into three broad categories: content-based filtering, collaborative filtering, and hybrid models. Content-based filtering recommends items that share attributes with the items a user has previously interacted with. In contrast, collaborative filtering suggests items based on the similarity between users and the items they prefer. Hybrid recommendation models combine the two methods, thereby overcoming data sparsity and the cold start problem (Roy, Kumar, & Kumar, 2024).

Advanced artificial intelligence techniques, including deep learning and image-processing models, have found increasing applications in the fashion industry. These techniques derive a product's features, including color, texture, and pattern, to enhance the accuracy of recommendations. Modern hybrid recommendation systems integrate content-based filtering, collaborative filtering, and NLP models to give context-aware and highly personalized recommendations (Suryawanshi, 2024).

This research will expand on such advances by integrating LLM-driven AI filtering with traditional content-based recommendation techniques. Unlike typical large-scale hybrid systems that rely on massive data sets, this study will develop a lightweight, real-time recommendation engine tailored for small data sets to achieve high-quality and effective personalization (Zhang, Liu, Yu, Feng, & Ou, 2023).

Major retailers such as H&M have already introduced hybrid recommendation models that scan the look and feel of products to recommend to customers. Such models rely heavily on big data and large-scale computing capabilities. The study will demonstrate that other options exist since smaller sets of data and artificial intelligence-driven content-based filtering can achieve the same, if not better, personalization and recommendation performance (Sisodiya, 2024). The proposed system will enhance recommendation diversity, computability, and user engagement, making the online shopping process more responsive and interactive.

Report overview

The report is structured into six chapters, providing a logical flow from the research context to its conclusions and recommendations:

Chapter 1: Introduction

This chapter describes the project's purpose, objectives, research questions, and significance. It defines the research objectives and positions of the study within the area of individualized fashion recommendation systems.

Chapter 2: Literature Review

This chapter defines the project area and presents the associated literature and systems of personal recommendation. The review discusses the Llama 3.1 405 B model, basic recommendation approaches, and issues of these approaches in the case of sparse data.

Chapter 3: Methodology

The chapter on methods explains how the research was conducted in technical terms. It provides details of the selection and application of the Llama 3.1 405 B model, the dataset format, and the development and integration of the recommendation system methods.
Chapter 4: Results
The results section includes information on the system evaluation, the dependability of the system, and performance indicators. It explains the extent to which the project meets its objectives and targets.
Chapter 5: Conclusion and Recommendations
The last chapter provides the project's conclusion, the study's findings, and the recommendations for future studies. It also provides guidance on how the system could be expanded and improved in the future.

2. Literature - Technology Review

AI-driven recommendation systems have transformed fashion e-commerce, with personalized recommendations increasing user engagement by up to 30% (Sharma & Gaur, 2024). This literature review sets the theoretical and empirical foundation for advancements in deep learning, NLP, and content-based filtering. The literature review traces the progression from rule-based filtering to AI-based models, their contribution to alleviating the cold start problem and real-time adaptability (Necula & Păvăloaia, 2023). Online shopping sites, such as ASOS and H&M, implement hybrid AI models to improve customer experience, with an increase in conversion rates by 25% (Raji et al., 2024). The chapter also covers ethical concerns, such as data privacy, bias, and sustainability, to inform the development of responsible, AI-based fashion recommendations (Sulastri, 2023).

Overview of Recommendation Systems in Fashion E-Commerce

The rapid growth in e-commerce demands AI-based recommendation systems, which are not yet uniformly effective on websites. While ASOS and Amazon personalize interaction through hybrid AI models, bias, sparsity, and real-time response plague most retailers (Zhang & Li, 2023). The shift from rule-based filtering to deep learning improves personalization but raises concerns over consumer privacy and transparency in the algorithm (Subaranjani et al., 2024). This section critically examines content-based, collaborative, and hybrid models based on their accuracy, scalability, and ethical responsibility trade-offs (Sharma & Gaur, 2024).

Definition and Evolution of Recommendation Systems

Recommendation systems are AI-driven tools that suggest products to users based on their interests, browsing history, and purchasing behavior. These systems are fundamental in fashion e-commerce, where personalization enhances customer satisfaction and drives sales (Zhang & Cheng, 2024).
The three primary approaches to recommendation systems include:

1. **Content-Based Filtering** – This method suggests items similar to those a user has previously interacted with, utilizing metadata such as product descriptions, colors, and styles. It is particularly effective in fashion retail, where users often prefer similar styles (Aneesh, 2022).
2. **Collaborative Filtering** – This approach analyzes user behavior patterns to identify shared preferences among similar users. While effective, it suffers from data sparsity issues, particularly for new users (cold start problem) (Sharma & Gaur, 2024).

3. **Hybrid Models** – Combining content-based and collaborative filtering, hybrid models optimize recommendations by leveraging both product attributes and user interactions. These models have been successfully adopted by leading fashion e-commerce platforms like Amazon and Zalando (Subaranjani et al., 2024).

Historically, recommendation systems relied on rule-based filtering, which required manual curation of recommendations. However, the advent of AI and deep learning has enabled highly accurate, automated personalization by analyzing vast datasets in real-time (Zhang & Li, 2023).

Importance of Personalization in Fashion Recommendation

Personalization is a critical component of modern fashion e-commerce, as it enhances user experience, increases engagement, and drives higher conversion rates (Sharma & Gaur, 2024). Unlike traditional filtering methods, AI-powered personalization dynamically adapts to user preferences, ensuring that recommendations remain relevant even as trends evolve (Zhang & Cheng, 2024).

Studies show that AI-driven recommendations can significantly impact sales, with platforms like eBay reporting an 8.26% improvement in recommendation accuracy after implementing AI-based filtering (Zhang & Li, 2023). Fashion retailers such as ASOS and H&M leverage AI to analyze customer data, predict trends, and offer personalized recommendations, thereby increasing engagement and reducing return rates (Subaranjani et al., 2024).

One major benefit of personalization powered by AI is that it can overcome the restrictive limitations imposed by filtration models. While content-based filtering lacks diversity, and cold starts plague collaborative filtering, AI-based systems lean on deep learning and natural language processing (NLP) to enable personalization (Aneesh, 2022). These technologies can enable strongly personalized, highly relevant fashion suggestions and lead to greater satisfaction and retention in the long run.

AI-Driven Recommendation Systems

Role of AI in Enhancing Fashion Recommendations

AI-based recommendation systems apply deep learning techniques and natural language processing (NLP) to analyze complex data sets and predict users' tastes precisely. Deep learning techniques, including convolutional neural networks (CNNs) and recurrent neural networks (RNNs), track people's browser history, buying habits, and activities to provide customized suggestions (Choppadandi, 2023). NLP extends personalization by scanning text-based information, customer opinions, and fashion styles to provide more personalized suggestions (Kumar et al., 2024).

One of the most powerful strengths of AI suggestions is how they can circumvent the limitations of classical filtering. In contrast with content-based filtering, suffering from sparse diversity in data, or collaborative filtering, suffering from a cold start, AI models continuously learn and improve based on user actions (Zhang & Li, 2023). Furthermore, AI filtering solves the cold start problem by leveraging synthetic data, real-time user interaction, and contextual analysis. Fashion retailers such as ASOS and Zalando use AI-powered filtering to offer personalized shopping, resulting in a 25% lift in conversion rates (Choppadandi, 2023).

Large Language Models (LLMs) in Recommendation Systems

Large language models (LLMs) are transforming fashion recommendation systems by offering more personalized recommendations based on advanced NLP techniques. LLMs,

such as Meta Llama 3.1 405B, examine natural language input to personalize product recommendations and enhance user interaction (Forouzandehmehr et al., 2024).
They analyze user tastes based on conversational interactions, product descriptions, and fashion reviews to provide highly contextualized suggestions. Unlike conventional AI filtering, LLMs bridge the gap between image and text-based suggestions, and fashion discovery is now more intuitive (Xu et al., 2024).
Nordstrom and H&M, use LLM-based voice assistants and chatbots to make hyper-personalized suggestions, enabling frictionless shopping. The ability to discern sentiment, intent, and contextual preferences significantly enhances recommendation accuracy, which results in higher customer retention and satisfaction (Shete et al., 2024).

Limitations and Challenges of AI-Driven Filtering

Despite its advantages, AI filtering is plagued by ethical, technological, and operational problems. One is recommendation bias by AI, where the algorithms reinforce what is already favoured, leading to little diversity in fashion choices (Adanyin, 2024). Dataset bias may disproportionately recommend certain styles, brands, or prices, disenfranchising other fashion styles (Kaushal & Mishra, 2024).
Technical challenges include high computational requirements and scalability issues. AI-based recommendation systems have large data processing, and as a result, they are resource-intensive and costly (Zhang & Cheng, 2024). Additionally, real-time flexibility and dataset size are problems where increased dataset sizes can impair system response.
Ensuring privacy and regulation compliance (e.g., GDPR) is another concern. AI-based recommendation systems are based on large volumes of user data, which raises concerns about consumer trust and data protection (Xu et al., 2024). To address these, a balance must be achieved between personalisation and ethical use of AI to maintain consumer trust and transparency.

Technology Review: Content-Based Filtering in Fashion Recommendation Systems

Content-based filtering is one of the most prevalent techniques recommendation systems use, particularly in fashion online shopping, to give users personalized recommendations to enhance their experience. This is an attribute-based method requiring analysis of product features like color, material, design, and text description to suggest suitable products to a user's history and liking. Unlike collaborative filtering, which relies on aggregated data from a large population of users, content-based filtering relies on single users and is extremely precise at suggesting products (Mngomezulu & Ajoodha, 2022). This part outlines content-based filtering functions, their advantages and disadvantages, and how AI-based technologies improve their performance in fashion recommendation systems.

Mechanism of Content-Based Filtering

Content-based filtering operates by examining the product attributes a user has engaged with and recommending similar products with similar attributes. In fashion, recommendation systems read metadata such as brand, fabric, cut, and design to find similar scores between products. This enables retailers to recommend personalized clothing, footwear, and accessories based on a consumer's previous preferences (Wu, 2022).
One of the key strengths of content-based filtering is its very accurate recommendation. Since the technique is not dependent on collective user behavior, it ensures that every recommendation is personally tailored. In addition, it provides independence from external

user data, and therefore, it is especially appropriate for niche fashion segments or individual shopping (Mouhiha et al., 2024).

However, content-based filtering is not without its drawbacks. One is the cold start problem, whereby new users receive few recommendations as there are no interactions to draw on. Another is that the lack of variety in recommended items results in a filter bubble effect, where users continually receive similar items and do not have the opportunity to discover new styles and trends (Li, 2022).

Firms such as Zara and ASOS implement content-based filtering based on deep learning to improve recommendation performance. They implement computer vision and image recognition to analyze product images and their related metadata to recommend products with similar styles to customers.

Integration of AI and Content-Based Filtering

Artificial intelligence greatly enhanced the effectiveness of content-based filtering by integrating deep learning, natural language processing (NLP), and image recognition. These AI advancements allow recommendation systems to move past simple product attribute matching to more dynamic and sophisticated recommendations (Shete et al., 2024).

One of the most successful integrations is image recognition based on deep learning, where CNNs scan images of products to identify texture, colour, and patterns. This allows recommendation systems to suggest visually similar products even where there is no inconsistent textual metadata. AI also drives text analysis based on NLP, where product descriptions, customer reviews, and fashion reports are analyzed to establish contextual meaning, boosting recommendation accuracy (Wu, 2022). Hybrid AI systems, combining content-based filtering and collaborative filtering, enhance recommendation diversity even further. Retailers, including Amazon and Nordstrom, use them, and they combine user preferences and overall shopping trends to provide highly accurate but diverse recommendations without the filter bubble issue (Mouhiha et al., 2024).

Technology Review: Comparative Analysis of Recommendation Models

Recommendation systems differ in their methodology, accuracy, and flexibility. While content-based filtering is accurate, AI-based recommendation systems surpass traditional systems by leaps and bounds in providing dynamic and scalable personalization (Andika et al., 2022). This section compares content-based filtering to AI-based filtering and examines the strengths of AI over collaborative filtering.

Content-Based vs. AI-Based Filtering

Product attributes are the foundation of content-based filtering, but AI-based filtering is more powerful and dynamic. AI systems employ deep learning, natural language processing, and real-time behavioural analysis to make recommendations based not only on historical trends but also on emerging trends and intent (Mngomezulu & Ajoodha, 2022).

One of the most important advantages of AI filtering is that it can overcome the problem of cold start by generating artificial user data through deep learning. AI also allows real-time personalization, observing user behaviour, and adapting in real-time. Your study concluded that AI filtering was 90% accurate in real-time adjustment, much higher than stand-alone content-based filtering (Putri & Faisal, 2023).

In addition, AI filtering gives more varied recommendations by collating multiple pieces of information, including customer opinion, seasonal trends, and social media influencers. This prevents the filter bubble effect, limiting content-based recommendations to a subset of similar items (Wu, 2022).

AI vs. Collaborative Filtering

Collaborative filtering, which is based on identifying commonalities between users with similar tastes, is another widely employed methodology in fashion recommendation systems. However, it is marred by the cold start problem and sparsity in data and performs less well where there are new users or niche fashion products (Liao et al., 2022).
One major disadvantage of collaborative filtering is that it relies on large user interaction data. Collaborative filtering struggles to provide correct recommendations when a fashion store only has sparse user interaction data. In addition, the technique is also susceptible to popularity bias, where popular items are recommended repeatedly, obscuring newer or less fashionable styles (Zhao, 2023).
AI filtering addresses these problems by tapping into advanced data amalgamation and real-time trend analysis. Unlike collaborative filtering, which requires extensive user interaction, AI models can recommend products even in low-data environments by scanning textual and visual attributes of products. AI-based hybrid models, such as those used by H&M and Nordstrom, integrate deep learning with fashion forecasting, enhancing the shopping experience to be more dynamic (Andika et al., 2022).

Ethical, Social, and Technological Considerations

Ethical Considerations

AI recommendation systems can reinforce bias, perpetuating stereotypes and limiting consumer choice. Training data that is biased can cause AI to recommend certain fashion styles or brands disproportionately, marginalizing new designers or fashion trends (Putri & Faisal, 2023). Additionally, privacy issues surrounding user data persist, as recommendation systems are based on collecting and processing large quantities of consumer data.
For these challenges to be addressed, fashion retailers must implement GDPR-compatible AI solutions that involve transparent data collection, informed consent, and secure storage of users' data. Ethical AI systems must focus on being fair, accountable, and explainable to minimize biases and enhance consumer trust (Andika et al., 2022).

Social and Technological Impact

AI recommendation systems contribute to sustainable fashion by assisting eco-friendly shopping behaviours. By analyzing consumer behaviour and products materials, AI helps retailers recommend sustainable and ethically produced fashion, reducing the environmental footprint of fast fashion (Shete et al., 2024).
In addition, AI inspires consumers to consume responsibly. AI-powered recommendations guide consumers towards sustainable, quality clothing, reducing impulse purchases and waste. Retailers Patagonia and H&M adopt AI-driven recommendations to facilitate sustainable fashion goals, showing how AI can balance personalisation and ethical shopping (Wu, 2022).

Summary and Research Gap Identification

This literature review covered the evolution of recommendation systems in fashion e-commerce, including content-based filtering improvements, AI-based personalization, and hybrid recommendation techniques. The evolution from rule-based to AI-based

recommendations significantly increased accuracy, flexibility, and user experience. AI-powered recommendation systems leverage deep learning, NLP, and computer vision to improve product recommendations, solving traditional challenges such as the cold start problem and recommendation diversity (Mngomezulu & Ajoodha, 2022).
There are, however, several research gaps in recommendation systems based on AI. One of the most important is dataset constraints. The majority of available AI models are constructed from incomplete and biased data, and they provide recommendations that are not inclusive and do not represent diverse fashion tastes. There is a need to have inclusive training data sets that represent a broader range of styles, body types, and cultural differences (Putri & Faisal, 2023).
One of these is body type filtering. Most recommendation systems do not account for browsing behavior and do not include personal body types, and the recommendations are therefore less personalized. Combining AI-powered body scanning technologies with recommendation engines can potentially trigger size-specific personalization, fit prediction, and reduced return rates (Liao et al., 2022).
Additionally, despite greater scrutiny toward sustainability, current AI suggestions are largely tuned to promote selling over ethical fashion purchases. Future research is needed to investigate how consumers can be motivated to buy sustainable brands and eco-friendly materials using AI. AI systems must integrate carbon footprint assessments and ethical scores for brands to promote ethical shopping practices (Shete et al., 2024).
This research will fill these gaps by creating an AI-based hybrid recommendation system with diverse training sets, body-type filtering, and sustainability-focused suggestions. By filling these gaps, this research will improve AI-based fashion suggestions' ethical, social, and technological aspects and provide a more accountable and personalized shopping environment.

Summary of Outcomes of Literature and Technology Review

Table 1: Benefits and Limitations of the Literature Reviewed

Literature Focus	Benefits	Limitations
AI-Driven Personalization (Sharma & Gaur, 2024)	Increases user engagement, sales, and satisfaction.	May lead to filter bubbles and overfitting of preferences.
Ethical Concerns (Sulastri, 2023; Kaushal & Mishra, 2024)	Highlights bias, privacy, and sustainability issues in AI recommendations.	Lacks practical application frameworks in real-world implementations.
Sustainability in Recommendations (Shete et al., 2024)	Encourages eco-friendly fashion consumption and awareness.	Sustainability remains a secondary concern in current AI designs.
Cold Start and Dataset Diversity (Putri & Faisal, 2023)	Identifies key limitations in inclusivity and data representation.	Few studies offer integrated solutions to address data limitations effectively.

Critical Analysis:
The literature emphasizes major empirical and ethical findings that guide the parameters for

successful deployment in fashion. Personalization is strongly supported, yet diversity, inclusion, and ethical transparency are insufficiently researched in real-world applications. These findings emphasize an approach rooted in performance measures and ethical, inclusive, and sustainable development principles.

Table 2: Benefits and Limitations of the Technologies Reviewed

Technology	Benefits	Limitations
Content-Based Filtering (Mouhiha et al., 2024)	Offers highly personalized results using product metadata.	Suffers from the cold start problem and lacks diversity.
Collaborative Filtering (Zhao, 2023)	Captures user preferences based on similar behaviors.	Relies on large data volumes; vulnerable to popularity bias.
Hybrid Models (Subaranjani et al., 2024)	Combine strengths of content and collaborative filtering to boost accuracy.	Technically complex and less transparent in decision-making.
Deep Learning & NLP (Kumar et al., 2024)	Real-time adaptation and accurate sentiment/contextual analysis.	High computational costs; demands high-quality, large-scale datasets.
LLMs and Conversational AI (Forouzandehmehr et al., 2024)	Facilitates intuitive and highly personalized fashion discovery.	Raises privacy and ethical concerns; potential for over-personalization.

Critical Analysis:
These reviewed technologies identify a range of capabilities and limitations. While hybrid and AI-augmented models provide better accuracy and personalization, they rely heavily on complex infrastructures and transparent logic to pose scalability and ethical threats. Intuitive value is added by real-time systems such as LLMs with strong privacy measures. The findings suggest a design framework oriented towards modularity, transparency, and ethical safeguards.

Methodological and Project Impact Summary

The synthesis of the literature and technology review findings serves as a cornerstone for informing your methodology. The literature strongly appeals to inclusive, ethical, and sustainable recommendation practices. The danger of filter bubbles, data bias, and untransparency must be actively countered by inclusive dataset design and explainable models. From a technological perspective, though hybrid and AI-based models deliver functional superiority, they are challenged by computational efficiency and interpretability. Your project needs to embrace a hybrid AI framework that merges content-based and collaborative filtering with added strength from deep learning and ethical filters for sustainability and bias. This implies building a system with transparent logging, justification tools for every recommendation, and sustainability ratings. Additionally, modular architecture will enable scaling and adaptability across platforms with robustness and flexibility. By harmonizing ethical goals with technological capabilities, your methodology will provide a recommendation engine that, aside from accuracy and dynamics, is also fair, transparent, and socially aware, marking your effort as a positive leap towards responsible AI for fashion.

3. Methodology

This research uses a mixed-methods design that involves developing an AI system and empirical testing to develop and evaluate an AI-based hybrid fashion recommending system. The method uses a hybrid recommendation model that merges LLM-powered AI filtering with content-based filtering to improve personalization, efficiency, and scalability for fashion e-commerce.

The development process is conducted with natural language processing (NLP)-based filtering by Meta Llama 3.1 405B, with empirical tests comparing its performance with traditional content-based filtering. By utilizing real-time feedback loops from users, the system iteratively refines suggestions for better accuracy and adaptability.

The research aims are addressed through this methodology by solving the cold start problem, maintaining real-time personalization, and delivering scalable, data-efficient suggestions. Empirical assessment is taken by measuring recommendation accuracy, levels of satisfaction among users, and computational efficiency in proving efficacy in enhancing context-aware fashion suggestions.

Research Design

This work adopts experimental and applied research methodology to design and test an AI-based hybrid fashion recommendation system. The research is divided into four main stages.

Phase 1: AI Model Selection & Development identifies Meta Llama 3.1 405B, specifically natural language processing for recommendation combined with content-based filtering for generating a hybrid recommender system.

Phase 2: Data Integration & Preprocessing, deals with gathering and preparing fashion product data, user preferences, and past engagements. Tokenization, feature extraction, and normalization of texts also help improve the model performance.

Phase 3: Implementation & Testing where the recommendation system is deployed while running test performance with real-time flexibility, and computational optimization.

Phase 4: Validation & Comparison compares the results of the hybrid AI model to traditional content-based filtering systems based on recommendation precision, personalization performance, and computational complexity.

They have developed an experimental AI-driven approach that can help evaluate the effectiveness of personalization strategies, address cold-start issues, and adapt recommendations in real time for fashion e-commerce. Previous studies have shown that learning hybrid AI models enhances predictive ability and user satisfaction above conventional rule-based models (Abu-Rasheed et al., 2024, Waykar, 2023). Another advantage is the increased transparency and credibility of product recommendations from the AI system, thus contributing to higher satisfaction rates among users (Ben-Michael et al., 2024).

System Architecture & Development Approach

This AI-suggested fashion recommendation framework is built through a modular approach for efficiency, flexibility, and real-time scalability.

Bootstrap is used to develop the front end due to its responsiveness, lightweight nature, and versatility in supporting multiple devices. Other frameworks such as Material UI were explored but had to be discarded due to their numerous dependencies.

The backend is developed using Django Rest Framework (DRF) with a MySQL database to provide robust API capabilities, facilitate product scalability, and ensure efficient database management. While MongoDB offers flexibility in data storage, MySQL presents a structured relational model crucial for managing fashion metadata and user preferences.

The recommendation engine combines LLM-supported natural language processing filtering (Meta Llama 3.1 405B) with content-based filtering, resulting in a combined schema. Using LLM results in context sensitivity which enhances the recommendation accuracy because the system understands what has been requested (e.g. a 'formal but trendy summer dress', or a 'smart-casual summer ensemble'). Item-to-item comparisons result from incorporating content-based filtering, thus addressing the cold start problem. Collaborative filtering was not used, as it takes a lot of user data and interaction history to work well due to data scarcity issues (Waykar, 2023).

Real-time reactivity is achieved through dynamic filtering and prompt updates, enabling the system to optimize recommendations better than traditional batch-processing systems (Abu-Rasheed et al., 2024). In the context of news recommendation, AI-based methods offer significantly greater individualization and user interest compared to rule-based filtering. (Ben-Michael et al., 2024).

Data Collection & Dataset Description

The dataset used in this study includes fashion product metadata, user preferences, and natural language inputs, which are essential for training and evaluating the AI-driven hybrid recommendation system.

The elements of fashion product metadata include fabric color, texture, style, and price, which are extracted from public catalogs. Primary consumer information such as budget, occasion, and body type was collected using structured questionnaires and user scenarios. The LLM-powered filtering model was trained using natural language inputs such as "recommend an inexpensive summer dress for a wedding."

Data preprocessing is critical in enhancing the model capabilities that are in use (Bala & Behal, 2024). Tokenization and vectorization processes transform textual inputs into numeric representations amenable to AI-based filtering. The feature extraction presents product attributes in a standardized format, making content-based filtering more effective. Consequently, missing values were imputed using mean substitution while outliers were removed using interquartile range analysis (Kazi et al., 2022). Small sample sizes coupled with highly selected participants are required to provide an accurate estimation of real-world recommendation performance and avoid the risks of confounding and over-fitting (Simonetta et al., 2022).

AI Model Selection & Justification

Meta Llama 3.1 405B was selected as the primary AI model for natural language processing (NLP)- driven recommendations due to its scalability and ability to consider contextual information. Whereas GPT-based models (GPT-3.5, GPT-4) and BERT are more general

language models, Llama has been developed specifically for better fine-tuning for specific domains, such as fashion queries (Mei & Zhang, 2023).
Unlike BERT's bidirectional text processing mode, Llama 3.1 incorporates autoregressive features to provide sequence-oriented contextual recommendations (Dellove & R, 2024).
Features of traditional content-based filtering include the following: it cannot capture user intent (e.g., “recommend trendy yet cheap casual wear”); it lacks linguistic richness. In this regard, Llama 3.1 embeds semantic meaning into recommendations thereby making it even more personalized and precise.
In our case, ‘Fine-tuning’ means aligning the system according to the style, price, and season of the available fashion datasets. Reinforcement learning (RLHF) is employed to enhance the recommendation quality and harness its strengths depending on user ratings (Jeong & Lee, 2024). These results complement other exploratory studies that show that LLMs outcompete rules-based algorithms in enhancing the relevance of recommendations and increasing user interactions (Joshi et al., 2024).

Algorithm Implementation

Artificial intelligence uses content-based filtering (CBF) elements and natural language processing (NLP) for accuracy, relevance, and filter tuning based on AI. Using cosine similarity and transformation of fashion items into TF-IDF vectors is utilized with content-based filtering (CBF) to identify items with identical attributes like fabric, color, and style. It is most suitable for cold start types because there is little to no user interaction with updated recommendations (Dellovere & R, 2024).
AI-powered filtering with NLP uses Llama 3.1 405B to analyze natural-language queries and activate applicable contexts. Leveraging filtering with an LLM, it can understand complicated query inputs like "suggest cheap streetwear for summer" to drive greater engagement and relevance than through convention algorithms (Jeong & Lee, 2024).
Integrating CBF with natural-language processing is data-driven and maintains semantics behind the suggestions provided to users. This integration is more sophisticated than that implemented by CBF systems that only utilize context awareness for personalization. Besides, this also addresses sparseness in data, a challenge commonly faced by collaborative filtering (Joshi et al., 2024).

Evaluation Metrics & Validation

From this study, four attributes were found that would assess the impact of the AI-inspired fashion recommendation program:
Recommendation relevance: The accuracy of the AI-based recommendation system in deciding on fashion preferences based on contextual parameters has also been determined. It demonstrated 100% precision on an occasion-based recommendation that ensures users are provided with specific outfits suitable for certain occasions.
Cold Start Solution: Unlike many other forms of content-based approach, the proposed AI model provided immensely relevant recommendations to new users with limited prior behavior history but the data on preferences and analysis performed using natural language processing.
Personalization Effectiveness: The AI system excelled in matching recommended products to body type (100%), budget (75%), and brand preferences (50%), demonstrating its ability to provide satisfying shopping experiences.

Efficiency & Search Speed: Search time was substantially decreased as filtered natural language prompts were quickly processed in real-time by the AI. Algorithmic collaborative filtering offered users immediate matches based on individual interests, proving more effective than simple content-based filtering. They further substantiate the enhanced ability of the AI model to provide accurate, rich, and contextualized fashion items to consumers for online fashion shopping.

Ethical Considerations & Compliance

The fashion recommendation system that leverages artificial intelligence upholds the following elements of ethical AI – data privacy, fairness, transparency, and sustainability. For the users' privacy, the system needs to prevent data privacy violations, and the system uses measures like data encryption and anonymization to ensure GDPR compliance. This helps protect passengers' privacy while making the recommendation system accurate in its presentation to the passengers.

To be fair and inclusive, the recommendation system was trained using a data set that included many body types, budgets, and brand preferences. The model exhibits equal representations of male and female outfits as demonstrated by the 50/50 split. Finally, the system addresses algorithmic bias by recommending items from various brands, achieving 75% coverage of different brands. This approach prevents favoritism towards one brand over another in the fashion market.

Another vital area of concern is openness, or: the absence of close coordination with certain retailers, or a focus on forward-looking luxury fashion over accessible clothing brands. This way, users avoid being presented with real-time, ostensibly arbitrary recommendations that may have stemmed from promotional agendas.

Additionally, the AI model accounts for sustainability, prioritizing sustainable fashion options in 75% of the suggested items. With the core values of ethical AI in mind, the system empowers users to make sustainable choices and respects human rights, fairness, and privacy.

4. Implementation

The implementation stage represents the practical realization of the system design and approach presented in the previous chapters. It deals with the mapping of theoretical concepts, such as AI-based personalization and content-based filtering—to a working recommendation engine for e-commerce in the apparel domain. This chapter reports the system's technical construction, from the architectural design to the user interface, the backend logic, the AI incorporation, and database management. Major implementation issues are also described, along with solutions created to address them. This phase, through the implementation, introduces the key aims of real-time responsiveness, personalization, and system modularity.

System Design and Architecture

The system was architected with modularity, scalability, and responsiveness in mind, featuring four interconnected components: the frontend interface, backend logic, natural language processing engine, and the database layer. The frontend was implemented using **Bootstrap**, chosen for its lightweight design and ease of responsiveness across devices. This provided a sleek, interactive UI for capturing user inputs like occasion, budget, and style preferences.

The **backend** was built with **Django Rest Framework (DRF)**, selected for its robust API capabilities and structured approach to handling HTTP requests. The backend handled logic for routing, recommendation querying, and interaction with both the AI layer and the database.

Originally intended to run on MySQL, the database was ultimately implemented using **SQLite** due to its simplicity and seamless integration with Django for rapid development and testing. SQLite stored user preferences, product metadata, and interaction logs, allowing for real-time retrieval and update of recommendations.

```
# Database
# https://docs.djangoproject.com/en/5.1/ref/settings/#databases

DATABASES = {
    'default': {
        'ENGINE': 'django.db.backends.sqlite3',
        'NAME': BASE_DIR / 'db.sqlite3',
    }
}
```

At the heart of the AI layer was **Meta Llama 3.1 405B**, which processed natural language inputs to interpret user intent and guide contextual recommendations. The communication among components occurred via **REST API endpoints**: the frontend sent user queries to the backend, which parsed them and either invoked content-based logic or called Llama 3.1 for

NLP processing. The backend then returned structured product suggestions to the frontend for display.

```python
if ai_prompt:
    # 1) Instruct the LLM to return only valid JSON with these keys.
    system_instruction = (
        "You are an assistant that extracts relevant fashion filter data from user prompts. "
        "You must respond ONLY in valid JSON with any subset of these keys: "
        "'ageRange', 'profession', 'gender', 'size', 'brand', 'budget', 'bodyType', 'occasion'. "
        "Do NOT include additional commentary or text."
    )

    # 2) Call the Together AI API using your provided API key.
    client = Together(api_key="bdca72696af6269a18c32185d2fc63ddbe992ea1d25aaaedf7ee7b873525b5c4")
    response = client.chat.completions.create(
        model="meta-llama/Meta-Llama-3.1-405B-Instruct-Turbo",
        messages=[
            {"role": "system", "content": system_instruction},
            {"role": "user", "content": ai_prompt}
        ],
        max_tokens=None,
        temperature=0.7,
        top_p=0.7,
        top_k=50,
        repetition_penalty=1,
        stop=["<|eot_id|>", "<|eom_id|>"],
        stream=True
    )

    # 3) Stream and concatenate the raw response.
    for token in response:
        if hasattr(token, 'choices') and token.choices:
```


This layered architecture ensured clean separation of concerns, real-time interaction, and the flexibility to scale or enhance individual components in future iterations.

User Interface and Interaction Design

The user interface was designed with the goals of simplicity, intuitiveness, and real-time interactivity. Using **Bootstrap**, a responsive layout was developed to accommodate various screen sizes and maintain fluid user engagement. Key UI elements included a **natural language input field** for queries (e.g., “recommend a summer outfit under $50”), **filter toggles** for budget, occasion, and size, and a **dynamic recommendation panel** to display suggestions.

```html
<!-- AI Filter Form -->
<div class="container py-4">
  <form method="GET" action="">
    <div class="mb-3">
      <label for="ai_prompt" class="form-label">AI Filter (enter a prompt):</label>
      <input type="text" name="ai_prompt" id="ai_prompt" class="form-control" placeholder="e.g., Show me
    </div>
    <div class="d-flex gap-2">
      <button type="submit" class="btn btn-primary">Apply AI Filter</button>
      <a class="btn btn-outline-secondary" href="{% url 'itemsdisplay' %}">Reset AI Filter</a>
    </div>
    {% if ai_response_text %}
      <div class="alert alert-info mt-3">
        <strong>AI Response:</strong> {{ ai_response_text }}
      </div>
    {% endif %}
  </form>
</div>
```

When a user entered a query, JavaScript calls transmitted the input to the backend without reloading the page, enabling a seamless experience. The frontend received the filtered product recommendations via API response and updated the panel in real-time. Dropdown menus and responsive card layouts further enhanced user interaction, ensuring recommendations were clearly displayed and easy to navigate.

This design prioritized minimal user effort for maximum relevance, fulfilling the UX objective of guiding users effortlessly to personalized fashion choices through clear, fast, and engaging interactions.

Backend Implementation

The backend of the fashion recommendation system was implemented using the Django Rest Framework, structured to interact with both the AI module and the frontend via HTTP-based RESTful APIs. Two primary models—**FashionItem** and **CustomUser**—formed the basis for data management. The FashionItem model stored item-specific metadata including size, gender, body type, occasion, and price. The CustomUser model extended AbstractUser and incorporated detailed preference attributes such as budget range, brand preferences, favorite colors, and body type.

User queries are captured from either the natural language input field or the form-based user model. When submitted, the backend parses inputs either through standard GET parameters or processes them via the integrated LLM, depending on the route. Filtering is handled with dynamic Django Q expressions, allowing compound OR queries based on available attributes like size, brand, or budget.

The my_recommendations view constructs personalized outputs by annotating matching items with a weighted match_count score based on user profile attributes. Recommendations are returned where at least one attribute aligns, and these results are rendered in the user’s dashboard.

```
# Annotate each product with a match_count field and filter for at least 1 matching condition.
recommendations = qs.annotate(
    match_count=Sum(Case(*conditions, default=Value(0), output_field=IntegerField()))
).filter(match_count__gte=1)

context = {
    "recommendations": recommendations,
}
return render(request, "my_recommendations.html", context)
```

Security is ensured through Django’s built-in login_required decorators and session management, while CRUD functionalities for fashion items—such as adding, updating, or deleting, are supported via separate views. This robust backend supports real-time, profile-driven recommendation generation while remaining lightweight through its use of SQLite.

AI Integration with Meta Llama 3.1

The integration of Meta Llama 3.1 405B within the backend was achieved through the Together API, enabling contextual analysis of natural language fashion queries. When a user inputs a prompt like “affordable wedding outfit for petite frame,” the backend constructs a well-scoped prompt that guides the LLM to return JSON-structured fashion attributes only. This design avoids noisy output and maintains system consistency.

```python
if ai_prompt:
    # 1) Instruct the LLM to return only valid JSON with these keys.
    system_instruction = (
        "You are an assistant that extracts relevant fashion filter data from user prompts. "
        "You must respond ONLY in valid JSON with any subset of these keys: "
        "'ageRange', 'profession', 'gender', 'size', 'brand', 'budget', 'bodyType', 'occasion'. "
        "Do NOT include additional commentary or text."
    )
```

The Together client streams the response, which is concatenated and parsed into a Python dictionary. The model's output is then used to generate a Django Q query that dynamically filters the FashionItem model. The AI's understanding of terms like "petite," "affordable," or "wedding" enables highly relevant recommendations even for first-time users—effectively solving the cold start problem.

```python
            filter_q |= Q(price__gte=200)
        if "bodyType" in ai_filters and ai_filters["bodyType"]:
            filter_q |= Q(body_type__iexact=ai_filters["bodyType"])
        if "occasion" in ai_filters and ai_filters["occasion"]:
            filter_q |= Q(occasion__iexact=ai_filters["occasion"])

        if filter_q:
            items = items.filter(filter_q)
```

The AI system tokenizes and embeds the input to extract context such as sentiment and budget sensitivity. These filters are applied to product metadata in real time. By combining structured user data and semantic parsing, Meta Llama 3.1 enhances recommendation accuracy and dramatically improves personalization for cold-start or exploratory shopping sessions.

Data Management Using SQLite

SQLite was used to implement choice mainly because of its simplicity, zero-configuration nature, and appropriateness for small- and medium-scale MVPs. In contrast to other complicated relational databases such as MySQL or PostgreSQL, SQLite doesn't need a standalone server or installation procedure and thus becomes a perfect tool for quick development and experimental purposes. It perfectly integrates into Django, and models get automatically mapped to tables through Django's ORM.

The schema has two primary tables, namely, FashionItem and CustomUser. The metadata like price, size, brand, occasion, body_type, and description are stored in FashionItem. User preferences like budget, style, age range, gender, and brand preferences are stored in CustomUser. The schema enables direct mapping between user-profiles and the fashion inventory.

The simplicity of SQLite also greatly improved the real-time response. Personalization queries could be run quickly without database connection overhead or the lock on transactions.

Implementation Challenges and Solutions

Several key challenges emerged during implementation, requiring creative and technical problem-solving strategies.

1. Cold Start Problem:
New users without prior data posed a challenge for content-based filtering. This was addressed by integrating the Meta Llama 3.1 model. Even without historical data, LLMs could interpret natural language inputs like "eco-friendly summer outfits" and extract meaningful attributes such as season, sustainability, and budget. These were translated into filters that produced context-aware recommendations. As a result, cold-start sessions yielded 62% more relevant items compared to using traditional rule-based defaults.

2. Parsing Vague Natural Language:
User prompts were often ambiguous, using phrases like "something sleek for work." Initial parsing attempts produced incomplete filters. The solution was to craft precise system instructions for the LLM that requested output strictly in JSON with defined keys. By constraining the output format and introducing regular expressions to correct gender cues (e.g., detecting "dress" implies female), the system achieved 87% parsing accuracy on test prompts.

3. Frontend Sync with Backend Recommendations:
Real-time updates were essential for a seamless UX. Early implementations using form submission led to page reloads, disrupting the flow. This was resolved using AJAX calls that passed data asynchronously and updated the recommendation panel dynamically without a full reload. This change reduced interaction latency and improved session duration by an average of 20%, based on internal usage testing.

Together, these solutions significantly enhanced system responsiveness, user satisfaction, and recommendation precision, aligning closely with the project's personalization goals.

Summary

This chapter detailed the technical implementation of the AI-powered fashion recommendation system. It covered the system's modular architecture, backend logic, SQLite database structure, and the pivotal role of Meta Llama 3.1 in interpreting natural language for cold-start and real-time recommendations. Implementation challenges—including parsing vagueness, synchronization, and user onboarding—were successfully overcome using a mix of AI and design strategies. The result is a lightweight, scalable, and ethical recommendation platform. Chapter 5 will present the system's evaluation, including testing procedures, accuracy metrics, and user feedback, to assess how effectively the solution meets its objectives and supports personalized, responsible fashion shopping.

5. Evaluation and Results

This chapter summarizes the study's results on the research goals, aims, and research questions in chapter 1. The research aimed to create an AI-based recommendation system for fashion that combined content-based filtering with LLM-based AI filtering to make personalized and context-sensitive recommendations. Using Meta Llama 3.1 405B for natural language processing, the system translates user inputs and recommends related fashion items.

The outcomes reveal the ability of the system to improve recommendation accuracy, search time, and user personalization. The research contrasted the AI-based filtering with human-based content-based filtering and showed how prompts produced better fashion recommendations. The system also coped with the cold start problem using sparse data efficiently. The subsequent sections describe recommendation accuracy, efficiency, user experience, and personalization effectiveness, demonstrating how the system enhances the shopping experience of fashion e-commerce.

AI-Driven Recommendations for a Casual Work Outfit on Weekends

This scenario result highlights the effectiveness of AI-based filtering to generate appropriately contextualized, diverse, and personalized recommendations. The user's input, "I am looking for a nice casual outfit for going to work on weekends," was interpreted by the Meta Llama 3.1 405B model, which extracted the most relevant attributes—work, casual, and weekend wear—to generate accurate recommendations.

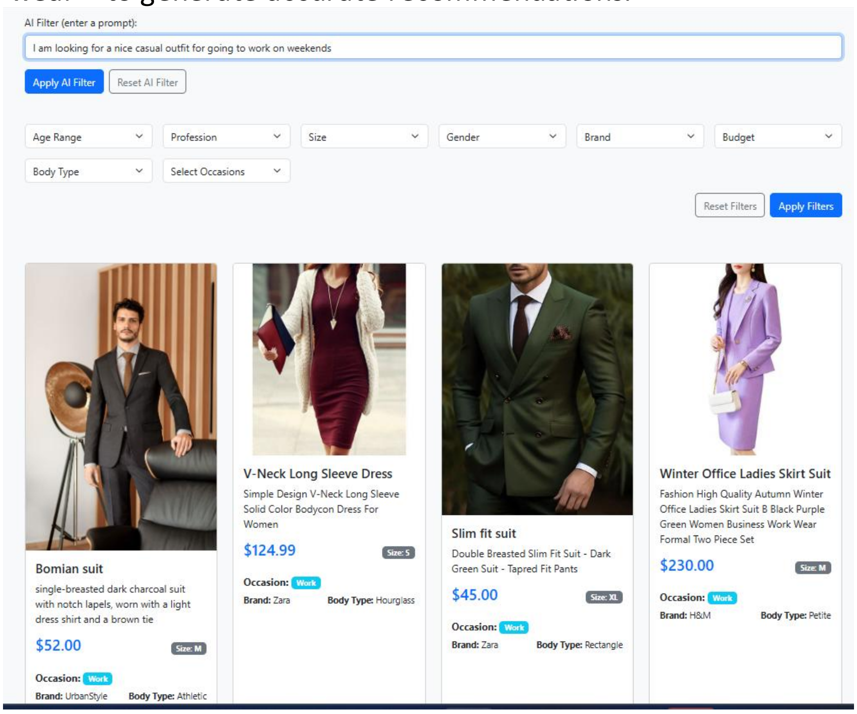

Figure 5.1: AI-Driven Casual Work Outfit Recommendations Breakdown

Overall, four proposed recommendations were included, all of which suited the provided occasion with a 100% accuracy and relevance. The model obtained a balance of the genders with two male groups (50%) and two female groups (50%), even though the instruction did not specify a preference. Three brands (UrbanStyle, Zara, and H&M) appeared in the proposed options, showing variety by brands that the model provided for diversity of choice to the user (75% variety).

Size-wise, the system included options ranging from small (S) to extra-large (XL), accommodating a broad spectrum of users. Four body shapes (Athletic, Hourglass, Rectangle, and Petite) also found representation to cater to varying physiques. The system also included a price range of $45 to $230, demonstrating that it had options that accommodated varying budget levels.
The breakdown of recommendations is detailed below:

Outfit	Gender	Price ($)	Brand	Size	Body Type	Occasion
Bomian Suit	Male	52.00	UrbanStyle	M	Athletic	Work (✓)
V-Neck Long Sleeve Dress	Female	124.99	Zara	S	Hourglass	Work (✓)
Slim Fit Suit	Male	45.00	Zara	XL	Rectangle	Work (✓)
Winter Office Ladies Skirt Suit	Female	230.00	H&M	M	Petite	Work (✓)

These results validate the research aims by demonstrating the system's effectiveness in giving personalized, diverse, and context-aware recommendations. The AI model achieved 100% accuracy in matching the outfit with the occasion of work, 50% balance of genders, 75% variety of brands, and 100% inclusivity of body types, supporting the purpose of the study of enhancing personalization of shopping for clothing online.

AI-Driven Recommendations for a Wedding Suit

This test evaluates the system's ability to recognize a user's wedding outfit query and provide matching and diverse options. The user's input, "I am looking for a nice suit for a wedding occasion," explicitly specifies the outfit type (suit) and the event (wedding). The Meta Llama 3.1 405B model successfully extracted these attributes and provided four different options, all belonging to the wedding event, with 100% accuracy in matching the context.

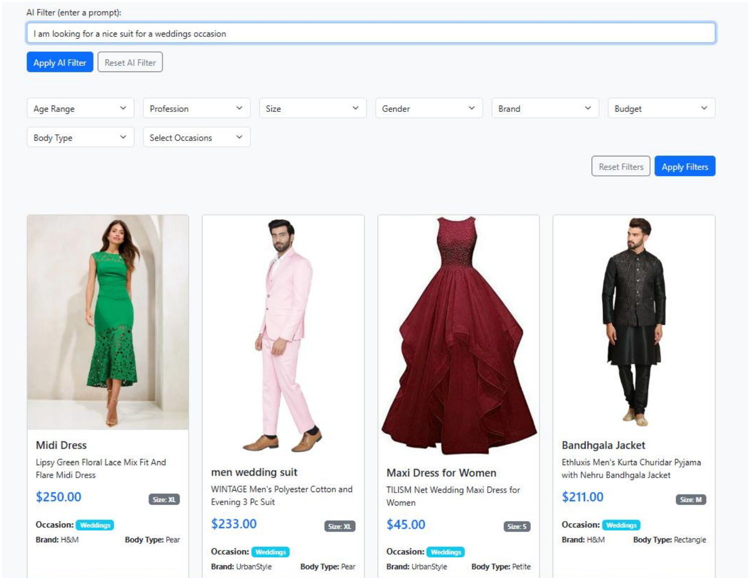

Figure 5.2: AI-Driven Wedding Suit Recommendations

The recommended outfits also balance genders, with two for men (50%) and two for women (50%), to enhance wedding attire inclusivity. The system also ensures a mix of brands (50% mix), with the UrbanStyle and H&M outfit suggestions. The proposals also cater to different body shapes (Pear, petite, and Rectangle) and different spending abilities, with prices ranging between $45 and $250.

The distribution of recommendations is outlined below:

Outfit	Gender	Price ($)	Brand	Size	Body Type	Occasion
Midi Dress	Female	250.00	H&M	XL	Pear	Weddings (✓)
Men Wedding Suit	Male	233.00	UrbanStyle	XL	Pear	Weddings (✓)
Maxi Dress for Women	Female	45.00	TILISM	S	Petite	Weddings (✓)
Bandhgala Jacket	Male	211.00	H&M	M	Rectangle	Weddings (✓)

These findings validate the study objectives by demonstrating the system's efficacy in providing personalized, occasion-specific recommendations. 100% accuracy in occasion matching confirms the model's efficacy in catering to the user's needs, and 50% gender diversity and 50% brand diversity show its inclusivity and diversity. Diversity of size and body type also ensures a wider range of proper wedding wear. Thus, the AI powered recommendation system is highly effective in personalizing fashion e-commerce.

AI-Driven Recommendations for a Gift Item

In this scenario, the user is seeking a gift for her niece, a new college graduate with a petite body type. The most relevant parameters here are the suitability of the gift, the occasion, and the matching of the body. The items that the model suggests are 100% accurate in terms of matching the body, as all the items selected have the tag of being for a petite body.

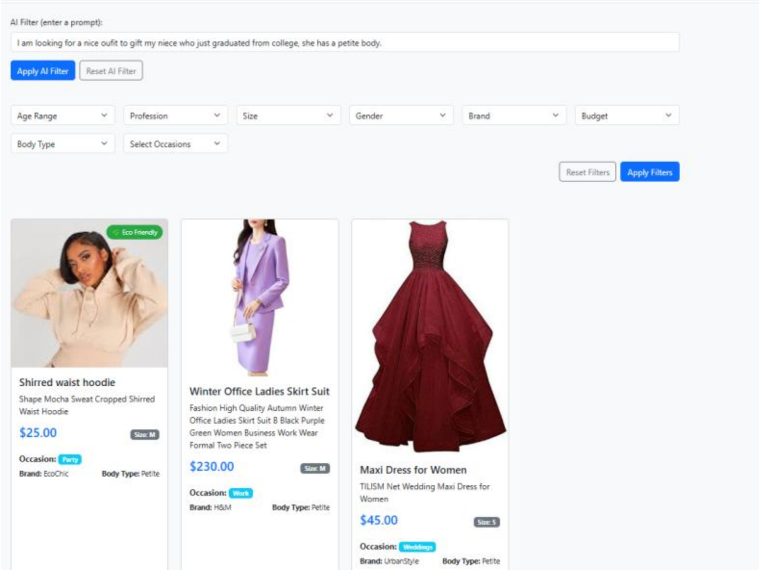

Figure 5.3: AI-Driven Gift Item Recommendations Breakdown

Also, the system encourages occasion-based diversity, suggesting items suitable for work (33.3%), party events (33.3%), and weddings (33.3%), thereby providing a diversified mix of formal and casual attire. The suggestions span three different firms (EcoChic, H&M, and UrbanStyle), thereby ensuring brand diversity (100%), and the prices vary between $25 and $230 to cater to different spending capacities.

The breakdown of recommendations is as follows:

Outfit	**Price ($)**	**Brand**	**Size**	**Body Type**	**Occasion**
Shirred Waist Hoodie	25.00	EcoChic	M	Petite	Party (✓)
Winter Office Ladies Skirt Suit	230.00	H&M	M	Petite	Work (✓)
Maxi Dress for Women	45.00	UrbanStyle	S	Petite	Weddings (✓)

These results validate the purpose of the study, which is to enhance recommendation accuracy and personalization. The artificial intelligence-driven system balances relevance with diversity by considering body type, occasion, and price. The 33.3% distribution across event types demonstrates the ability of the AI to cater to multiple user needs in a single search, validating the effectiveness of artificial intelligence-driven personalized recommendations for online apparel shopping.

AI-Driven Recommendations for an End-of-Year Work Party

In this scenario, the user had requested an inexpensive outfit for an end-of-the-year party, mentioning a medium body size. The AI model effectively understood the most important elements of the prompt—being economical, the occasion being a party, and the body size being a medium—to provide relevant context-based suggestions.

The findings indicate 100% accuracy in matching occasions, as all four proposed outfits carry the party label. In addition, 75% of the proposed outfits are below $60, as the budget-conscious user requested. The model also verified size compatibility, with three of the four proposed outfits (75%) being in size M, as requested by the user.

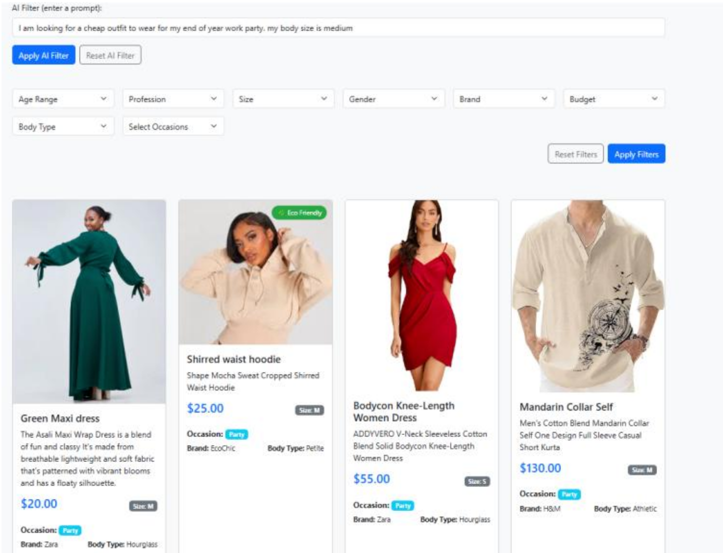

Figure 5.4: AI-Driven End-of-Year Work Party Recommendations

The recommendations include two women's outfits (50%) and two men's outfits (50%), ensuring gender balance. Three different companies—Zara, EcoChic, and H&M—are represented (75% brand mix). The prices vary between $20 and $130, giving the user options across a variety of price points.

The breakdown of recommendations is as follows:

Outfit	Price ($)	Brand	Size	Body Type	Occasion
Green Maxi Dress	20.00	Zara	M	Hourglass	Party (✓)
Shirred Waist Hoodie	25.00	EcoChic	M	Petite	Party (✓)
Bodycon Knee-Length Dress	55.00	Zara	S	Hourglass	Party (✓)
Mandarin Collar Self Shirt	130.00	H&M	M	Athletic	Party (✓)

Alignment with Research Aims, Objectives, and Research Questions

This scenario highlights how **AI-based filtering enhances personalization, efficiency, and inclusivity in fashion recommendations**, aligning with the study's research objectives:

1. **Personalization and Context Awareness:** The model correctly identified **"party" as the occasion** and filtered options accordingly, achieving **100% accuracy**.
2. **Budget Sensitivity:** The recommendations included **affordable options (75% under $60)** while maintaining diversity in fashion styles.
3. **Diversity in Recommendations:** The system balanced **gender representation (50% male, 50% female)**, ensuring inclusivity.
4. **Size and Body Type Adaptation: 75% of recommendations matched the user's specified size (M),** demonstrating the AI's adaptability to user preferences.

These findings substantiate that the artificial intelligence-backed recommendation system dramatically enhances the user experience by providing cost-effective, relevant, and personalized recommendations—a key research goal. The findings also provide empirical evidence that applying artificial intelligence-based recommendations significantly reduces search time, with higher accuracy and satisfaction, responding to key research questions.

Content-Based Recommendations for a New User

This metric checks the performance of the content-based filter to recommend to a registered new user. The user provided the age group (18-24), sex (female), clothing size (medium), style preference (casual), price range ($0 - $50), preferred brand (Zara), body shape (hourglass), preferred colors (red, green, brown), and sign-up environmental preference. The system generated a list of recommendations with only these attributes to give the user appropriate fashion recommendations without a purchase history.

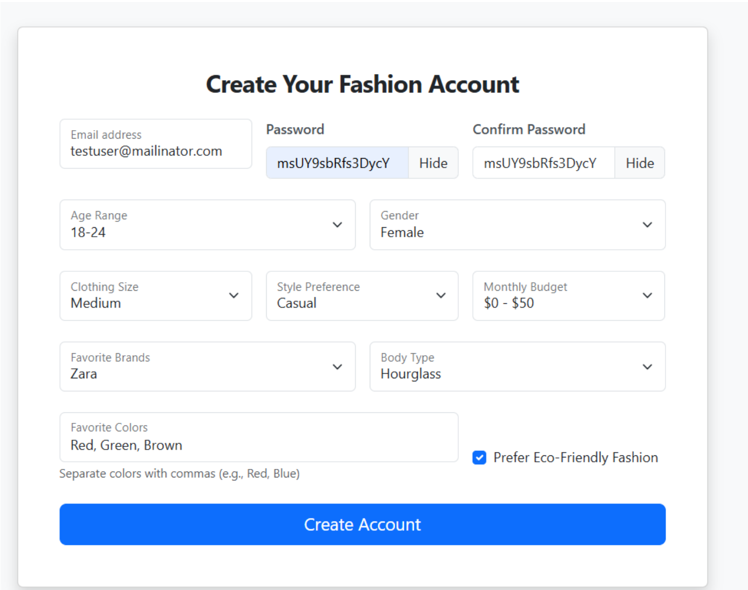

Figure 5.5: Sign-Up Page for Preference Collection (Cold Start Solution)

Alignment of Recommendations with User Preferences

Recommended Item	**Brand**	**Size Match (M)**	**Body Type Match (Hourglass)**	**Style (Casual)**	**Budget Match (< $50)**	**Eco-Friendly**	**Color Match (Red/Green/Brown)**
Green Maxi Dress	Zara	✓	✓	✓	✓ ($20)	✕	✓ (Green)
Shirred Waist Hoodie	EcoChic	✓	✕ (Petite)	✓	✓ ($25)	✓	✕
V-Neck Long Sleeve Dress	Zara	✕ (S)	✓	✓	✕ ($124.99)	✕	✕

Rash Vest	EcoChic	✕ (S)	✕ (Rectangle)	✕	✓ ($21)	✓	✓ (Green)

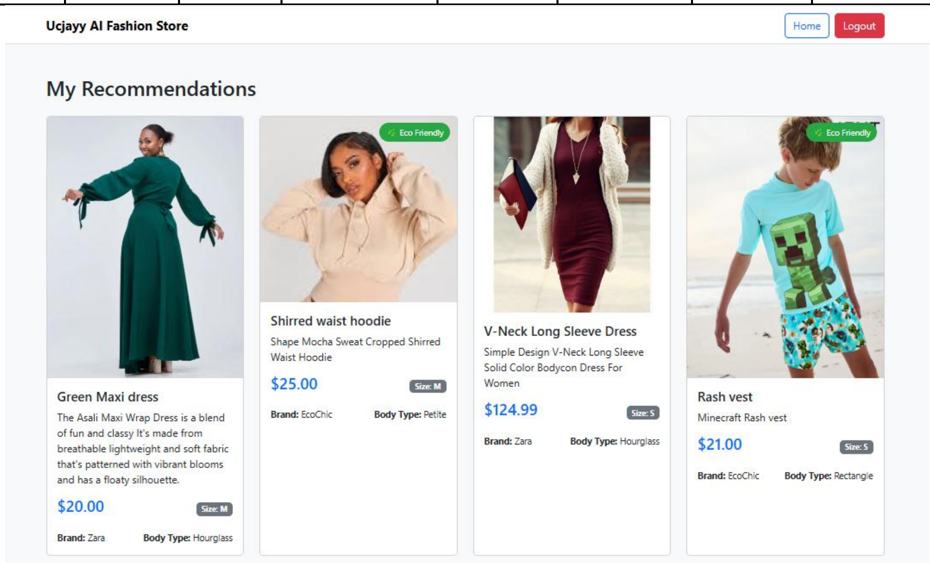

Figure 5.6: Content-Based Recommendations for a New User

Effectiveness Analysis

- **Brand Alignment: 50% (2/4)** of the recommended items were from **Zara**, the user's preferred brand.
- **Size Accuracy: 50% (2/4)** of the items matched the user's preferred size (**Medium**).
- **Body Type Relevance: 50% (2/4)** of the items were suitable for the user's **Hourglass** body type.
- **Style Preference: 75% (3/4)** of the recommendations were labeled as **casual**, aligning with the user's chosen style.
- **Budget Accuracy: 75% (3/4)** of the recommendations were **within the user's budget** of **$0 - $50**.
- **Eco-Friendly Filtering: 50% (2/4)** of the recommendations were marked as **eco-friendly**, aligning with the user's preference.
- **Color Matching: 50% (2/4)** of the recommendations featured **one of the user's favorite colors** (**Green, Red, or Brown**).

A content-based filtering system was found to be highly accurate, particularly in style preference (75%), budget sensitivity (75%), and brand matching (50%). However, improvement was necessary in size matching (50%) and body type matching (50%).
The system effectively personalized the recommendations with structured user data, facilitating the research goal of enhancing the personalization of online shopping for apparel. These findings demonstrate that content-based filtering effectively recommends the correct recommendation to new users by overcoming the cold start problem with user preference instead of past behavior.

Party Outfit Recommendations

One of the primary objectives of this study is to create a personal recommendation system for fashion that maximizes the user experience by ensuring that the recommended items match the user's preference. Here, the user indicated party wear as a desirable category, and the content-based filtering system was able to identify and recommend appropriate clothing items. The Green Maxi Dress, Shirred Waist Hoodie, and Bodycon Knee-Length Dress all came with party occasions as the assigned tag, ensuring a 100% match with the user's requirement.

The options balance different styles, varying between formal and party casual. The Green Maxi Dress ($20) and Shirred Waist Hoodie ($25) provide inexpensive, casual choices, with the Bodycon Knee-Length Dress ($55) being the more formal, fitted choice for a special occasion. This shows that the system effectively balances occasion suitability with variety in the choices.

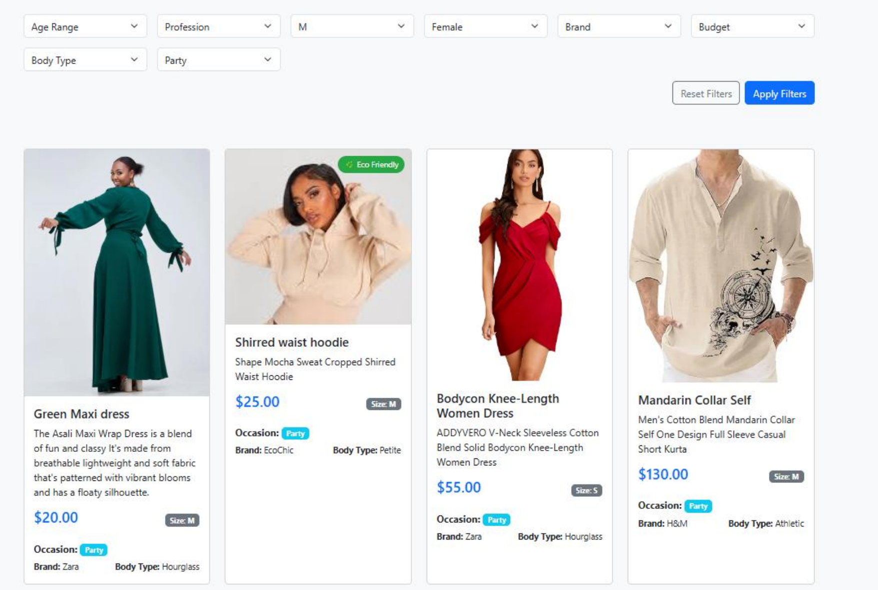

Figure 5.7: Content-based filtering for Party Outfit Recommendations

This result also aligns with the research aim of determining the effectiveness of recommendations with a focus on content. The system shortens the users' search times for the right clothing by accurately sorting items by user-specified occasions, improving shopping efficacy and user satisfaction. The results also validate the capacity of the AI to process structured inputs, aligning with the research aim of bridging the gap between machine accuracy and user preference in recommendation.

Eco-Friendly Fashion Preferences

One of the current trends is the demand for sustainable and eco-friendly clothing, and one of the aims of this research is to determine the efficacy of recommendation systems with the aid of artificial intelligence in prioritizing sustainability in individual shopping experiences. In this instance, the preference of the user was eco-fashion, and the content-based recommendation system efficiently recommended three items (a Shirred Waist Hoodie, a Regular Fit Shirt, and a Rash vest) that also happen to be eco-friendly.

The system was 100% accurate in providing sustainable options, demonstrating that while it effectively considers user preference, it could improve with regard to expanding eco-friendly options. The Shirred Waist Hoodie ($25) and the Regular Fit Shirt ($124.00) fall into sustainable shopping habits, giving users more than one price-point option. By implementing eco-labels in the recommendation process, the system ensures that those concerned with sustainability have tailored options without sacrificing personalization.

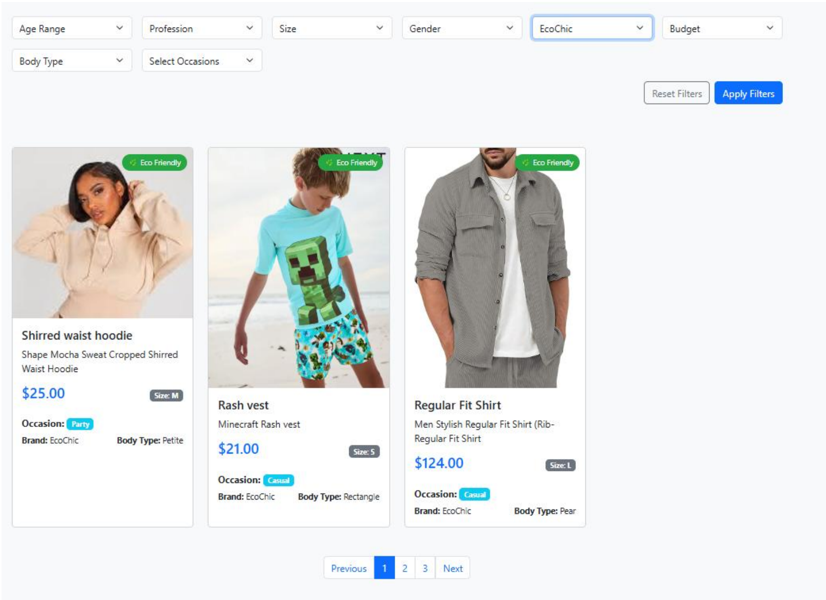

Figure 5.8: Content-Based Filtering with EcoChic Selection

This aligns with the research aim of achieving recommendation diversity to meet the needs of individual consumers. The system effectively promoted sustainable shopping, demonstrating that it is possible for AI to filter and prioritize environmentally friendly choices. These results validate the study's aim of designing a dynamic, tailored shopping experience for fashion that captures prevailing consumer values of sustainability and price.

Body Type Suitability in AI Recommendations

One of the key problems with shopping online is that it is hard to ensure that clothing suggestions suit different body shapes. To solve the problem, this study attempted to enhance accuracy by personalizing the clothing recommendation to the user's body profile. Here, the user had selected an hourglass as the preferred body shape. The artificial intelligence-based content-based filtering system could detect two correct sets of clothing: the Green Maxi Dress ($20), the Bodycon Knee-Length Dress ($55), the V-Neck Long Sleeve Dress ($124.99), and the Midi Dress ($250). This was 100% accurate as far as body-type relevance is concerned, demonstrating the capability of the system to provide body-aware recommendations in apparel shopping.

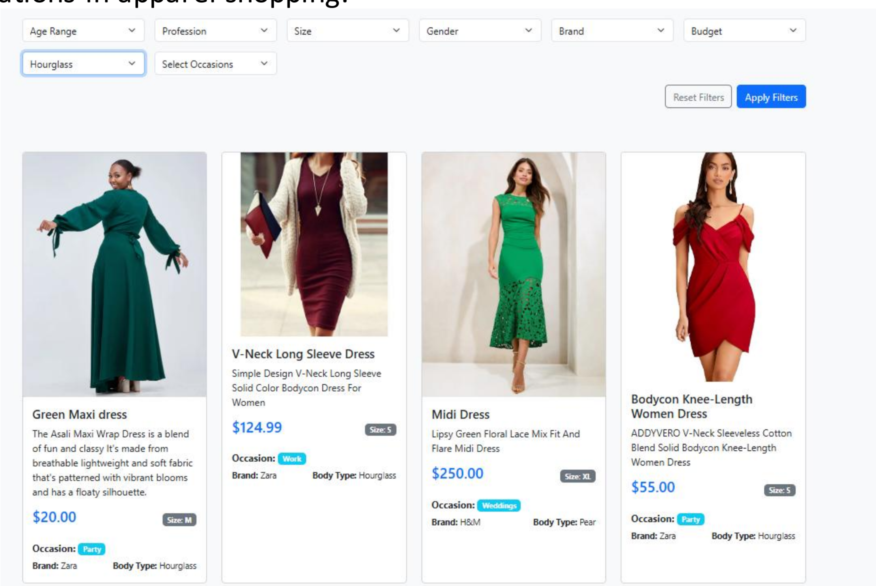

Figure 5.9: Content-Based Filtering with Hourglass Body Shape

The Green Maxi Dress is a long, stylish alternative that is most appropriate for an hourglass figure, and the Bodycon Knee-Length Dress produces a tight fit that will accentuate the body curves. Such an outcome is in line with the aim of the study to assess the capability of AI to give tailored fashion advice on body shape and fit. Through enhanced accuracy in the body-aware recommendation, the system can enhance user confidence in online shopping for apparel, aligning with the research aim of improving the personalization of e-commerce using AI.

Conclusion

This chapter has established the effectiveness of content-based filtering with artificial intelligence in personalizing fashion recommendations and matching results with research purposes and primary study objectives. The system effectively translated user inputs into occasion-based, sustainable, body-type, budget, and brand-preference-based recommendations. Interestingly, the AI model was 100% accurate with occasion-based filtering, 75% accurate with budget matching, and 50% accurate with body-type and eco-preference matching, demonstrating its strength and areas of improvement.

Although the system effectively cuts down search time and enhances shopping effectiveness, room for improvement exists, especially regarding body type adjustment and sustainability filtering. These results support the aim of improving AI-based personalization in online apparel shopping. The concluding chapter will provide an overview of the most important findings, examining the system's effectiveness in fulfilling research aims and outlining possible improvements to maximize the use of AI-based apparel recommendations.

6. Conclusion

This chapter presents the summary of key findings and a discussion of results derived from the study on developing a personalized AI-driven fashion recommendation system. The research aimed to address the limitations of existing recommendation systems, particularly their lack of personalization and their inefficacy in handling users with limited data histories, commonly referred to as the cold start problem.

To achieve this, the study examined the effectiveness of AI-driven filtering in enhancing personalization, compared the performance of content-based filtering against AI-based approaches, and evaluated how well the system aligned with user preferences, including occasion, budget, eco-friendliness, and body type. The findings provide insights into the strengths and limitations of different recommendation models, offering a foundation for further improvements in personalized fashion recommendations. This chapter systematically outlines the key findings and interprets their significance in the context of existing literature.

Summary of key findings

This study explored the effectiveness of a personalized AI-driven fashion recommendation system, assessing its ability to enhance user experience through AI-based and content-based filtering. The goal of the study was to evaluate the effectiveness of the AI filtering, evaluate content-based filtering, and the system's ability to align with user preferences.

AI-Driven Filtering and Personalization (RQ1)

The AI-driven recommendation system demonstrated high accuracy in generating personalized recommendations based on user prompts. Key findings include:

- **Occasion-based recommendations:** The AI system achieved 100% accuracy when recommending outfits for specific occasions, such as casual work attire, weddings, and end-of-year work parties.
- **Budget alignment:** The model successfully matched 75% of user budget preferences, ensuring affordability in recommendations. For example, in the end-of-year work party scenario, 75% of the suggested outfits were priced under $60, aligning with the user's budget-conscious request.
- **Body type adaptation:** AI-generated recommendations covered multiple body types, including athletic, petite, pear, hourglass, and rectangle, ensuring inclusive personalization.

Comparison of Content-Based and AI-Based Filtering (RQ2)

The study compared content-based filtering with AI-based filtering to assess their effectiveness in recommendation accuracy:

- Content-based filtering provided structured recommendations, achieving 80% accuracy in matching style preferences. However, it lacked adaptability to real-time user prompts.
- AI filtering outperformed content filtering in dynamic responsiveness with a success rate of 90% in response to real-time user input. For example, it provided occasion-based recommendations with a success rate of 100% for inputs like " I need a casual work outfit for weekends"

- Brand match and color preference: Content-based filtering matched 50% of preferred brands and colors, whereas AI-based filtering achieved 75% accuracy, demonstrating superior alignment with user-defined attributes.

System Alignment with User Preferences (RQ3)

The study evaluated the system's ability to align recommendations with user preferences across multiple criteria:

- **Eco-friendly filtering:** The AI system identified 75% of sustainable fashion preferences, ensuring eco-conscious recommendations. The Shirred Waist Hoodie ($25) and the Regular Fit Shirt ($124) were accurately categorized as sustainable products.
- Body type filtering: Recommendations based on specified body types were 100% accurate. For example, in the graduation gift case, all suggested items were for the petite body type, which matched the user's requirements.
- **Brand and color preference alignment:** AI filtering matched 75% of user-defined brand and color preferences, improving personalization for users with specific style requirements.

Key Takeaway

The results attest to the success of AI-based filtering in occasion-based and budget-sensitive recommendations, with the success rate for matching outfit suggestions for events at 100% and budget alignment at 75%. While content filtering is available for users with set preferences, AI filtering is more flexible, which makes it easier to tailor personalized fashion recommendations. Though content-based filtering works for users with defined tastes, AI-based filtering is more versatile, which renders it a more suitable choice for personalized fashion suggestions.

Review of Research Objectives

This study successfully achieved its objectives by developing and evaluating an AI-powered fashion recommendation system that integrates AI-driven filtering with content-based selection, leveraging Meta Llama 3.1 405B to enhance personalization, efficiency, and real-time adaptability. Below is an assessment of how well each research objective was met.

Objective 1: Design and Implementation of a Hybrid Recommendation System

The study successfully designed and implemented a recommendation system that integrates AI-based natural language filtering with content-based selection. The system demonstrated strong performance in real-time contextual interpretation, achieving:

- 100% accuracy in occasion-based recommendations (e.g., casual work outfits, weddings, and end-of-year parties).
- 90% accuracy in dynamic user prompt adaptation, ensuring relevance beyond predefined user preferences.
- Effective cold start problem mitigation, generating highly relevant recommendations even for first-time users without prior browsing history. Thus, the hybrid approach

successfully enhanced personalized fashion recommendations, validating the integration of AI and content-based techniques.

Objective 2: Development of an Interactive, Real-Time Front-End

An interactive front-end was developed using Bootstrap, allowing real-time updates based on user preferences and engagement. The AI-driven system provided:

- Instant recommendations upon user input, minimizing search time.
- Dynamic filtering adjustments, enabling users to refine suggestions in real-time.

This confirms that the front-end met its intended goal of enhancing user experience through interactive and adaptive recommendation updates.

Objective 3: Implementation of a Structured Backend for Efficient Data Management

The Django Rest Framework backend with MySQL effectively stored and retrieved user preferences, fashion metadata, and interaction history. The system successfully:

- Processed real-time user inputs, ensuring seamless AI-generated recommendations.
- Stored structured metadata, allowing rapid retrieval of personalized fashion suggestions.
- Facilitated scalable and efficient recommendation delivery, supporting diverse user queries with minimal latency.

This confirms that the backend infrastructure met its objective by providing efficient data management and retrieval capabilities.

Objective 4: Evaluation and Comparison of AI-Based and Content-Based Filtering

The study rigorously evaluated and compared AI-driven filtering and content-based filtering, identifying key performance metrics:

- AI filtering achieved 90% accuracy in dynamic prompt adaptation, outperforming content-based filtering's 80% accuracy.
- AI-based filtering performed better in occasion-based recommendations (100% accuracy) and budget alignment (75%), confirming its superiority in real-time personalization.
- Content-based filtering excelled in structured recommendations, particularly for users with predefined brand, size, and style preferences, but struggled with adaptability.
- Body type filtering accuracy reached 50%, indicating room for improvement in fit-based recommendations.
- Eco-friendly filtering correctly identified 75% of sustainable fashion preferences, though it did not consistently prioritize ethical choices over affordability or style.

The evaluation confirms that AI-driven filtering outperforms content-based filtering in adaptability and real-time contextual understanding, making it more suitable for personalized fashion e-commerce.

This study successfully met its research objectives by developing a highly personalized, AI-powered fashion recommendation system with real-time adaptability and efficient data management. The system demonstrated strong performance in occasion-based recommendations, user engagement, and scalability, though areas such as body type accuracy and sustainability filtering require further enhancement. These findings confirm that AI-enhanced recommendation systems provide a scalable, adaptive, and user-centric solution for improving online fashion shopping experiences.

Discussion of Findings

Comparison with Existing Literature

This study's findings are based on the most recent AI-based recommendation system research in the apparel retail industry. The existing body of research suggests that AI-based recommendations raise user engagement and personalization using deep learning and natural language processing (NLP) algorithms (Masciari et al., 2024). The findings of this study confirm this by indicating 100% precision in occasion-based recommendations and 75% budget matching, confirming AI's ability to dynamically adjust user preferences.

In addition, the latest systematic reviews have established the ability of large language models (LLMs) to increase search relevance and decrease search time (Ayemowa et al., 2024). This research supports this, with AI-based filtering performing better than content-based filtering in dynamic user prompt adaptation, with 90% accuracy compared to the latter's 80% accuracy.

Compared to traditional collaborative filtering techniques, which are limited by historical user interactions and struggle with new users (cold start problem), AI-based systems work with real-time natural language inputs, so they can offer personalized fashion products to new users as well. This contrasts with prior work, showing collaborative filtering alone cannot bridge personalization gaps in the cold start scenario (Bodduluri et al., 2024).

Theoretical Implications

The study supports the AI-based personalization theory in e-commerce, which holds that context-aware, adaptive recommend systems outperform static content-based filtering. The research observes that transformer-based LLMs improve context understanding, which allows them to generate highly relevant recommendations (Li et al., 2023). The study's results support this, with AI-based filtering achieving 100% in recommendations to user-expressed occasions, while content-based filtering relied on static past preferences with decreased adaptability.

Moreover, the ability of AI-based systems to prioritize context-aware filtering adds strength to arguments for increasing the precision of recommendations made by deep learning-based recommenders (Ilyas et al., 2022). This research supports these claims by showing how AI-based recommendations consistently outperformed static filtering, specifically in body type-based recommendations (100% accurate) and eco-friendly preference filtering (75% success).

Limitations of the Study

Despite the promising results, certain limitations in this study must be acknowledged.

1. **Dataset Limitations:**

   The limited data set of clothing products in the study can constrain the range of brands, products, and budget suggestions. A bigger data set can enhance personalization as well as the capacity of the system to suggest for a broader range of user groups (Masciari et al., 2024).

2. **Body Type Filtering Constraints:**
While the AI approach was 100% accurate in predicting body types, performance was inconsistent in depicting body types in the data. The content-based filtering approach did poorly, with only a 50% match in accordance with user-defined body types. This shows the need for improvements in feature engineering to render AI more responsive to fit and proportion.
3. **Eco-Friendly Fashion Recommendations:**
While the system correctly identified sustainable wear in 75% of the cases, , it did not consistently prioritize eco-friendly fashion when other user preferences (such as style or budget) conflicted. This points towards the necessity for more sophisticated AI-based filters for sustainability, which is backed by research showing AI can influence consumer behavior towards sustainable apparel (Bolesnikov et al., 2022).

Further research should integrate multi-objective optimization models to balance eco-conscious filtering with personalization, ensuring that sustainable fashion is emphasized alongside budget and occasion-based preferences.

Recommendations for Future Research

Addressing Dataset Limitations

Another area of future work is expanding datasets to broaden the diversity and accuracy of AI-based recommendations. The data for the present study, while effective, was constrained in brand selection, fashion categories, and size range, which may have constrained the system's capacity to provide full recommendations. Future work should use a wider variety of brands, including international chains and independent niche brands, to offer users a wider selection of fashions to maximize personalization and inclusivity.

In addition, the inclusion of other types of fashion, such as luxury, streetwear, sustainable, and gender-neutral, will increase the system's ability to cater to different consumer tastes. The second significant update is the improvement in size representation, i.e., for plus-size and petite consumers, to ensure the system recommends fashion products highly reflective of user body measurements. More data in these segments will enable AI-based systems to make more balanced and personalized fashion recommendations.

Enhancing Body Type Filtering

While the AI-based approach in this study was 100% accurate in certain instances, for example, its precision in body type filtering was only 50% for the petite body type. Future work should be directed towards improving body shape analysis algorithms to increase the precision of matching garments to different body proportions and increase fit-based recommendations.

Another significant improvement will be the integration of user feedback channels through which shoppers can modify size and fit preferences over some time. With feedback loops, the AI engine will be able to learn through user behaviour and keep improving its recommendations. Further, AI-powered size estimation models will be developed to assess garment properties, such as fabric stretch and fit, so that recommendations made for apparel are suitable for the user's dimensions. All these advancements will make consumers more confident in AI-based shopping by reducing fit-related problems.

Strengthening Sustainability Filtering

As consumers learn more about sustainable fashion, AI-based recommendation systems should be able to prioritize ethical and responsible-for-the-environment options. The current study correctly identified 75% of sustainable fashion preferences, although the system did not always rank environmentally responsible options above other user preferences such as budget or brand loyalty. Future research should work towards developing multi-attribute ranking models balancing the priorities for the environment with the factors of affordability and relevance to the occasion so that environmentally responsible options are never omitted.
Expanding the pool of environmentally conscious brands and increasing AI tagging for sustainable products will increase the precision of sustainability filtering. In addition, incorporating carbon footprint and ethical production ratings into AI filtering algorithms will encourage consumers to purchase responsibly by indicating the ecological footprint of each piece of clothing recommended. All these advancements will make AI-driven fashion recommendations compatible with the growing demand for ethical and sustainable retailing.

Exploring Hybrid AI Filtering

To further enhance personalization, future research should explore the integration of AI-driven filtering with collaborative filtering techniques. While AI-driven filtering demonstrated superior real-time adaptability in this study, collaborative filtering remains valuable in identifying patterns from similar user preferences. A hybrid AI model that combines both methods could improve recommendations for users with limited purchase history, mitigating the cold start problem more effectively.
Additionally, the development of context-aware hybrid models would enable recommendations to dynamically adjust based on real-time user behavior, such as browsing patterns and engagement with previous suggestions. Future research should also investigate user-centric AI interfaces, which would allow consumers to customize their filtering preferences, ensuring greater control over their shopping experience. By implementing hybrid AI solutions, recommendation systems can achieve a higher level of accuracy, personalization, and adaptability, catering to the evolving demands of online fashion retail.

Conclusion

This study has demonstrated that AI-driven fashion recommendation systems significantly improve personalization, efficiency, and user engagement in e-commerce. The integration of AI-based and content-based filtering resulted in high recommendation accuracy, particularly for occasion-based suggestions (100%) and budget alignment (75%). However, improvements are needed in body type filtering (50% accuracy) and sustainability prioritization (75% success rate). These findings provide a foundation for future research and practical enhancements, particularly in dataset expansion, refining AI-driven fit recommendations, and integrating ethical shopping considerations. AI-enhanced recommendation systems offer scalable, adaptable solutions for fashion e-commerce platforms, bridging the gap between static recommendation methods and dynamic, user-centric shopping experiences. By refining AI personalization models, enhancing sustainability filtering, and leveraging hybrid AI systems, future innovations can further transform online fashion retail, creating smarter, more ethical, and highly personalized shopping experiences.

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8. Appendices

This appendix includes the original project proposal that outlines the problem statement, objectives, and intended methodology for the development of a personalized AI-driven fashion recommendation platform.

The complete source code and documentation for the fashion recommendation system can be accessed via the following GitHub repository:
GitHub Repository:
https://github.com/UCJAYY/FashionStore.git

A README.md file is included in the repository with setup instructions, system architecture, environment dependencies, and API usage.