PERSONALIZED AI SHOPPING COPILOT

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Abstract— It is evident that online shopping has evolved greatly in recent years, thanks to platforms like Amazon and Flipkart that have fostered advanced recommendation engines and meaningful search features. These systems do a decent job of browsing and indexing an enormous amount of user data to recommend products, but are not without their drawbacks. Often, they depend only on exact keywords, show fixed lists of items, and don't let shoppers explore in a natural, conversational way. The personalization sometimes feels surface-level, and many users hesitate to trust recommendations because the process behind them isn't always clear. What's more, shoppers usually can't mix text and images easily when searching, something that would make exploring products feel a lot more intuitive and enjoyable. This paper introduces the "Personalized AI Shopping Copilot," a fresh kind of shopping helper designed to make the experience more interactive and personal. Imagine telling the system what you're looking for or snapping a quick photo, and it instantly gets both. It feels like chatting with a friend who really listens and adjusts to what you say as the conversation goes on. Instead of overwhelming you with long, dull lists, it takes the time to explain why certain products stand out, helps you easily compare options side by side, and even puts together smart bundles. That way, shopping feels clearer and more accessible and something you can trust. It also responds quickly and smoothly, with every cycle. This AI Shopping Copilot refactors the normal flow of search and filter. It offers shoppers a more conversational, personal way to discover products. The point is to make shopping transparent and personalized and even genuinely pleasurable, building real trust on every visit.

Index Terms— ***AI Recommendation Engine, Personalized Recommendation, Large Language Models (LLMs), Multimodal AI, Bundled Suggestions.***

I. INTRODUCTION

Over the past twenty years, online shopping has changed the way people purchase products. Platforms like Amazon, Flipkart, eBay, and Alibaba now help millions of customers daily, offering product choices like no other physical store can match [5]. A big part of their success comes from recommendation systems, the algorithms that suggest what you would like to buy next which is based on their shopping habits [7][9][10]. Traditionally, these systems either examine what similar customers have bought or focus on product features [11]. Search tools also play an important role, that guide users based on previously used keywords and recommend a huge list of items [3][12].

Which is very useful, but today's recommendation systems still feel mechanical and less conversational [6]. A typical online journey often begins with typing a keyword, scrolling through a fixed list of suggestions, and starting over if results don't match [3][9]. This makes platforms feel more like search databases than shopping companions. Shoppers today increasingly want something more engaging like having a knowledgeable assistant who helps them discover what they really need [1][2].

Current search tools fail in several ways. They depend too much on specific keywords, which doesn't help when users only have indefinite ideas, like "a jacket similar to one I saw on Instagram." So, the results are static, this makes the sorting process slow [5]. Personalization is only clear in history and misses the sentiment or intention of the recent situation [6]. Worse still, recommendations often appear as a black box, with no explanation of why items were suggested—leading many shoppers to feel sceptical [8].

The major difference lies in the lack of flexibility. People naturally combine words and visuals when describing what they want, maybe uploading a photo of a shirt and asking for something similar under a budget [3][4]. Today's systems rarely combine image and text in one seamless query, leaving interactions unnatural and restrictive [5][9].

These challenges open the door to a better approach. Conversational and multimodal AI research shows that systems which interact more like humans can build trust, responsiveness, and even enjoyment [1][2][8]. Bringing explainability into recommendations can make suggestions feel transparent and reliable [5][6]. Allowing people to mix words, context, and visuals creates a much more natural way of shopping [3][4][9].

There, Personal AI Shopping Copilot comes to work. Instead of providing static lists, it enables meaningful conversations between both, allowing users to improve queries step by step [1][2][4]. It can interpret both text and images, elaborate on its suggestions, and use groups or comparisons to support decision making [3][5][9]. Built on a scalable, cloud-ready system with a user-friendly interface, it is designed to provide instant, trusted, categorized, and tailored purchasing assistance [6][8].

In short, the Shopping Copilot shifts the entire experience from keyword-based searching to guided, conversational discovery [1][2][5]. It makes shopping online not just functional, but engaging, transparent, and human-like, helping people feel understood while turning browsing into a personalized journey rather than a tiring task [6][8].

II. OBJECTIVES

The primary goal of this project is to create and implement a Personalized AI Shopping Copilot that makes online shopping more interactional, easy to use and manageable. Unlike traditional e-commerce systems that mostly rely on fixed keyword searches, this project focuses on creating a conversational assistant that can understand natural human language and improve its responses through back-and-forth interactions. The main goal is to enable multimodal search, where users can provide input not just through text but also through images, allowing the assistant to better understand their needs. Another key aspect of the project is to provide explainable recommendations. This means the system will be able to show users why a particular suggestion was made, which helps build trust and makes the shopping experience more transparent. The project also aims to include product comparisons and smart bundling, so users can make better-informed choices. On top of that, the system is designed to offer real-time personalization, adapting to individual user preferences and the flow of conversation, making the overall shopping experience more engaging and user-friendly.

III. EXISTING METHODOLOGY AND DRAWBACKS

In the former years, top e-commerce platforms like Amazon and Flipkart invested a lot in building large-scale recommendation engines to improve customer experience. These systems tend to use collaborative and content-based filtering, and machine learning along with tools like Kafka, Spark, and Hadoop [14]. For example, Amazon has conquered analysing the browsing history, clicks, and purchase patterns to suggest relevant items. Similarly, Flipkart uses some deep learning models like VisNet in order to analyse product images and improve the search accuracy. Although these methods have increased the effectiveness, they remain monodirectional. The user enters a keyword, the system immediately ranks the products, and static lists appear as results. The interaction ends there, leaving no possibility for natural conversations to take place.

Several research studies and prototypes have tried to enhance this experience. Fu et al. [1] has highlighted how human demeanour, such as empathy and social presence, when introduced in chatbots can help customers to build trust, however too much anthropomorphism might fail. Similarly, Sidlauskiene et al. [2] conveyed that manlike verbal prompts in AI-powered chatbots affect the consumer's perception that in turn makes interactions feel more personal. Badave et al. [3] developed an e-commerce platform that combines a recommendation engine, chatbot, and reverse image search tool to reduce information overload and to improve usability. Rahevar and Darji [4] worked on survey data from Indian e-commerce users and came to a conclusion that AI-driven chatbots can significantly improve the process of product selection by increasing accuracy, engagement, and trust.

Further studies have expressed the need for AI-driven personalization and transparency. Valencia-Arias et al. [5] mentioned how chatbots would be able to provide real-time recommendations and decision support with the use of natural language processing and machine learning, while Priya and Bhagat [6] touched on how that speed and availability of chatbots enhance user satisfaction, even though there exist challenges in personalization and trust-building. Dwivedi et al. [7] studied recommendation systems with the Amazon data and worked on finding their potential for better decision-making and also discovering issues with contextual understanding. Similarly, Illescas-Manzano et al. [8] found that the usefulness and responsiveness of chatbots increase trust in sellers, which boosts brand preference and purchase intention.

From a machine learning view, Haque [9] showed that Random Forest models perform better than traditional classifiers in recommendation tasks, while Udokwu et al. [10] suggested a hybrid system that combines association rule mining and clustering to enhance cross-selling and targeted personalization.

Despite these developments, present day systems still depend on keywords heavily, and are often unclear and uncertain, with limited possibility for interactive or explainable recommendations [15]. This study shows that in recommendation technology, platforms like Amazon and Flipkart have created benchmarks, however they still behave like transactional tools in preference to conversational assistants. Chatbots and reverse image search are partial solutions that are favourable but aren't transparent and user friendly. Therefore, a strong need for a Personalized AI Shopping Copilot arises, that addresses these drawbacks by providing multimodal, conversational, explainable, and personalized recommendations, that convert online shopping into an engaging experience.

IV. PROPOSED METHODOLOGY AND FEASIBILITY STUDY

The solution proposed presents a Personalized AI Shopping Copilot that converts online shopping into an interactive and conversational proceeding instead of the old, static, keyword-based process that it has been so far. A conversational AI layer, fueled by large language models such as LLaMA or DialoGPT, forms the heart of the system. Unlike conventional search engines that return mere lists of products, this conversational layer communicates with the users in natural language. It narrows down queries over several exchanges. For instance, if one searches for "a casual blue shirt under ₹2000," the assistant can reply, "Would you like full sleeves or half sleeves?" This would help in providing more apt and context-specific suggestions.

One of the main features of the system is its ability to analyse and understand several forms of input, not just text but also images. Shopping in real life usually depends on visual cues, and to simulate this, the copilot utilizes CLIP (Contrastive Language–Image Pretraining) to produce joint embeddings of images of products and text descriptions. It utilizes Sentence-BERT as well to encode the semantic meaning of natural language queries. These models combined together enable users to apply text and image inputs with ease. For example, users can input a product image alongside conditions such as price, brand, or style. This multimodal strategy mimics the way humans tend to think about products, making the shopping process more natural [3].

This recommendation system has been tailored to provide more than just a simple list of products. It provides intelligent results through product comparisons, bundled suggestions, and explanations for its recommendations. For example, if the user has uploaded an image of a watch, then the system will recommend similar watches at a budget comfortable to the user and also suggest a compatible belt or wallet as a bundle. It also provides an explanation for every recommendation, like "This product is matching your uploaded image and within your budget." This makes users build trust and make better decisions [6].

To support good performance and scalability, the system utilizes Firebase Firestore for storing data, successfully dealing with product metadata, embeddings, and user interactions. Backend services, developed using FastAPI or Firebase Functions, receive requests from the AI models and handle the required business logic. On the frontend, a chat-like interface built using React and Tailwind CSS provides an intuitive experience. Users can enter queries, add pictures, and obtain results in real time. Deployment-wise, the architecture takes advantage of Vercel for frontend hosting and Google Cloud for backend services to ensure scalability and rapid responses across devices.

From an implementation perspective, the system is feasible and can be achieved using available technologies. Most of the needed AI models—CLIP, Sentence-BERT, and LLaMA—are already in open-source pre-trained form, which helps save time and money in development. Cloud services such as Google Cloud provide instant access to GPUs, and Firebase and Vercel provide low-cost deployment solutions for academic ventures as well as for real-world applications. The modularity of the system makes it possible to test, scale or upgrade each and every element separately without disturbing the overall system.

In general, the proposed method overcomes the shortcomings of the existing recommendation systems in the field of e-commerce by utilising multimodal, conversational and explainable AI recommendation systems [9], [10]. The feasibility study has demonstrated that this solution is technically feasible, cost efficient and scalable and hence this is a viable solution that enhances the overall online shopping experience.

V. ARCHITECTURE DIAGRAM AND SYSTEM MODULES

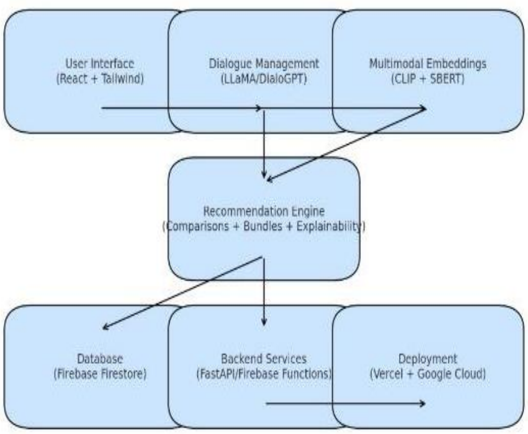

Fig 6.1 System architecture of the Personalised AI Shopping Copilot

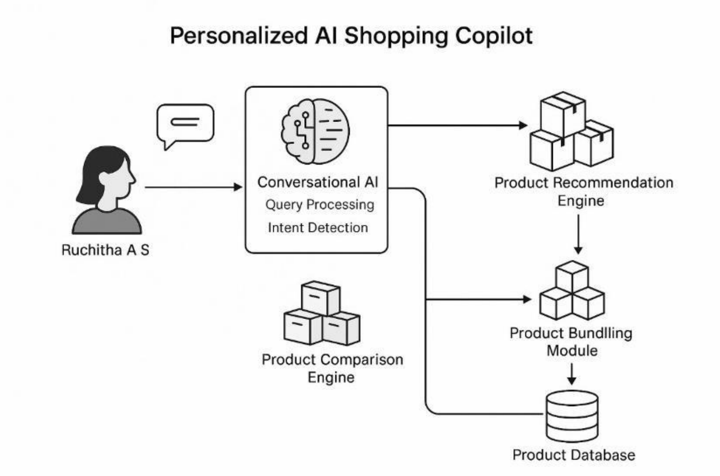

Fig 6.2 Workflow of the Personalised AI Shopping Copilot

The proposed project Personalized AI Shopping Copilot is divided into several modules , each module plays an important role in the performance of the system. All these modules work together to provide a seamless and intelligent shopping experience for the user as seen in Fig 6.1.

Each module deals with particular tasks which are combined to final software.

The User Interface Module serves as the front-end of the system, which is designed for user interaction with the system. It presents a responsive, chat-like interface allowing users to input the queries, upload the product images, and can receive real-time recommendations in return. This module is built using React and tailwind CSS, ensuring a consistent and effortless user experience across both desktop and mobile platforms. To make the user feel like they are communicating with a salesman instead of a recommendation engine this system imitates human language.

The Dialogue Management Module is the core for the dialogue assistance. It is responsible for understanding user input, keeping a track of the conversation and generating the proper responses. Language models like LLaMA (Large Language Model Accelerator) and DialoGPT (Dialogue Generative Pre-Trained Transformer) are used to develop this module. These models make the conversation more natural and human-like. Instead of behaving like traditional chatbots which are static, the system can handle multi-step dialogues, allowing the assistant to improve search precision, clarify doubts, and remember user intentions throughout the conversation.

The Multimodal Embedding Module is a core component of the system. It contains both visual and text information within the system. It mainly has two models. CLIP (Contrastive Language-Image Pre-training) is used to understand the relationship between text and images. It learns by predicting which text description matches with the specific images from the large dataset. The next model is BERT(Bidirectional Encoder Representations from Transformers) used for a wide range natural language processing(NLP) tasks because it excels at understanding the context of words within text, enabling applications like sentiment analysis, question answering, text classification, and targeted search.

Next module is Recommendation Engine Module which is used to generate the intelligent responses like personalised product lists, product comparisons, and also bundled suggestions. Rather than just showing random items, it creates smart and personalised outputs like for example comparing two smartphones based on features and prices. The uniqueness in this module is its transparency. Because it explains why each product is recommended. This confirms the system is trustable, helpful and user-friendly.

The Database Module plays an important role in supporting the recommendation systems. It stores all the product related information such as metadata, embeddings, and records of user interactions. Firebase Firestore is chosen to manage all these tasks, due to its fast performance, scalability and cloud-friendly. Having a well organised database ensures that it remains both accurate and efficient, regardless of the size of the product inventory.

At the end, the system's scalability, reliability and cost efficiency is handled by the Deployment and Infrastructure module. The processing of requests from the AI models and managing the business logic is done by backend using FastAPI or Firebase Functions. The frontend runs on Vercel, while Google Cloud provides the backend infrastructure, storage, and computing power needed for inference. We used tools like Vercel to develop the Frontend. The backend requirements and computing power is provided by Google cloud, so that it supports multi users with no latency.

Together, these modules create a balanced architecture where each component plays a key role as seen in Fig 6.2. The modular design ensures flexibility, meaning that improvements to one module, such as upgrading the recommendation engine or changing the interaction model, can be included without disturbing the entire system. This makes personalized AI shopping copilot not only effective but also future-proof.

VI. IMPLEMENTATION AND RESULTS

1) The hardware and software requirements for this project were selected to make sure everything runs smoothly and without any lag. On the hardware side, users can easily access the system from any device, like a smartphone, tablet, or computer, as long as they have an internet connection. Since AI-related work can be quite heavy, cloud infrastructure that includes GPU-enabled virtual machines on Google Cloud. These are mainly used for training and running models like CLIP, Sentence-BERT, and LLaMA. Along with that, Firebase Firestore Storage is used to keep product data, embeddings, and user activity logs safe and organized.
2)
3) For the software part, the frontend is created using React.js, which helps in building a fast and user-friendly interface. Tailwind CSS used for styling the frontend. The backend is built using FastAPI, it is a Python framework that can handle AI requests quickly. Firebase functions is used to manage the database. In the AI section, models like CLIP are used to connect images with text, Sentence-BERT is used to understand natural language queries, and LLaMA or DialoGPT is used for managing conversations with users. These models are built and run using PyTorch and Hugging Face Transformers, which make the process simpler and more flexible. For storing data, Firebase Firestore is used as it is a reliable NoSQL database, and Google Cloud Storage is used for keeping large files such as images and trained AI models safe. The frontend is hosted on Vercel for easy deployment and automatic updates, while the backend runs on Google Cloud Platform (GCP) to handle GPU-based AI tasks and make sure the system stays fast, stable, and available to users everywhere.

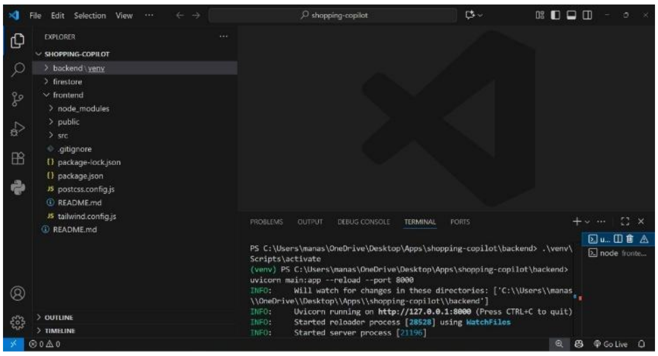

Fig 9.1 VS Code environment of the Personalised AI Shopping Copilot

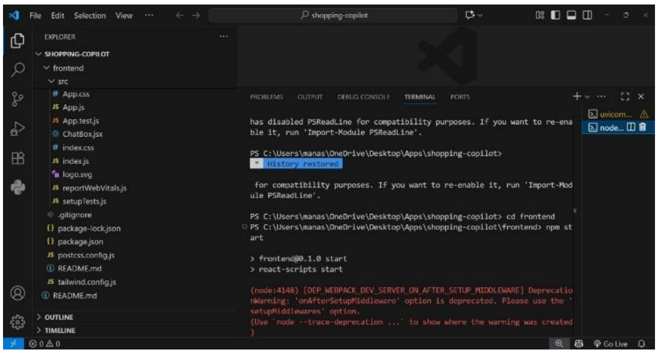

Fig 9.2 Implementation of frontend in VS Code environment

A.Frontend

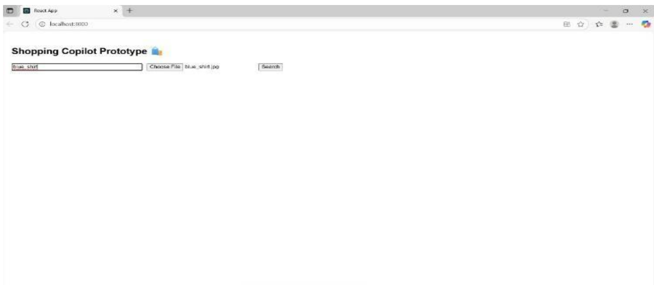

Fig 9.A.1 Prototype for basic frontend of the Copilot

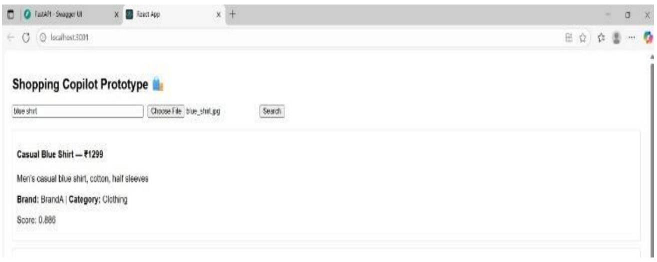

Fig 9.A.2 Prototype for basic output display in the frontend

B. Backend

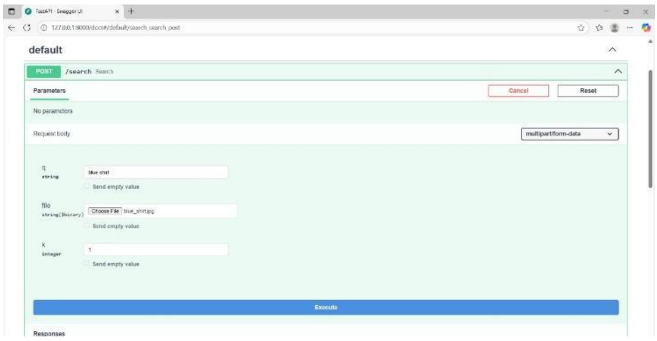

Fig 9.B.1 Backend using FastAPI

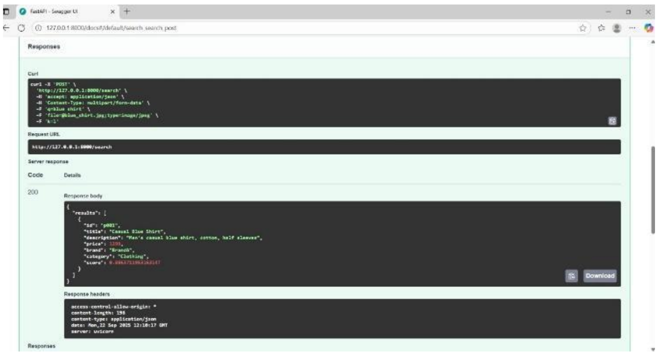

Fig 9.B.2 Data stored in json format in FastAPI

Conclusion

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singular heading even if you have many acknowledgments. Avoid expressions such as “One of us (S.B.A.) would like to thank ... .” Instead, write “F. A. Author thanks ... .” **Sponsor and financial support acknowledgments are placed in the unnumbered footnote on the first page**.

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