A Project Report on

"AI-Powered E-commerce Product Recommendation System"

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COMPUTER SCIENCE & ENGINEERING

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DEPARTMENT OF COMPUTER SCIENCE & ENGINEERING
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Certificate

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"AI-Powered E-commerce Product Recommendation System"

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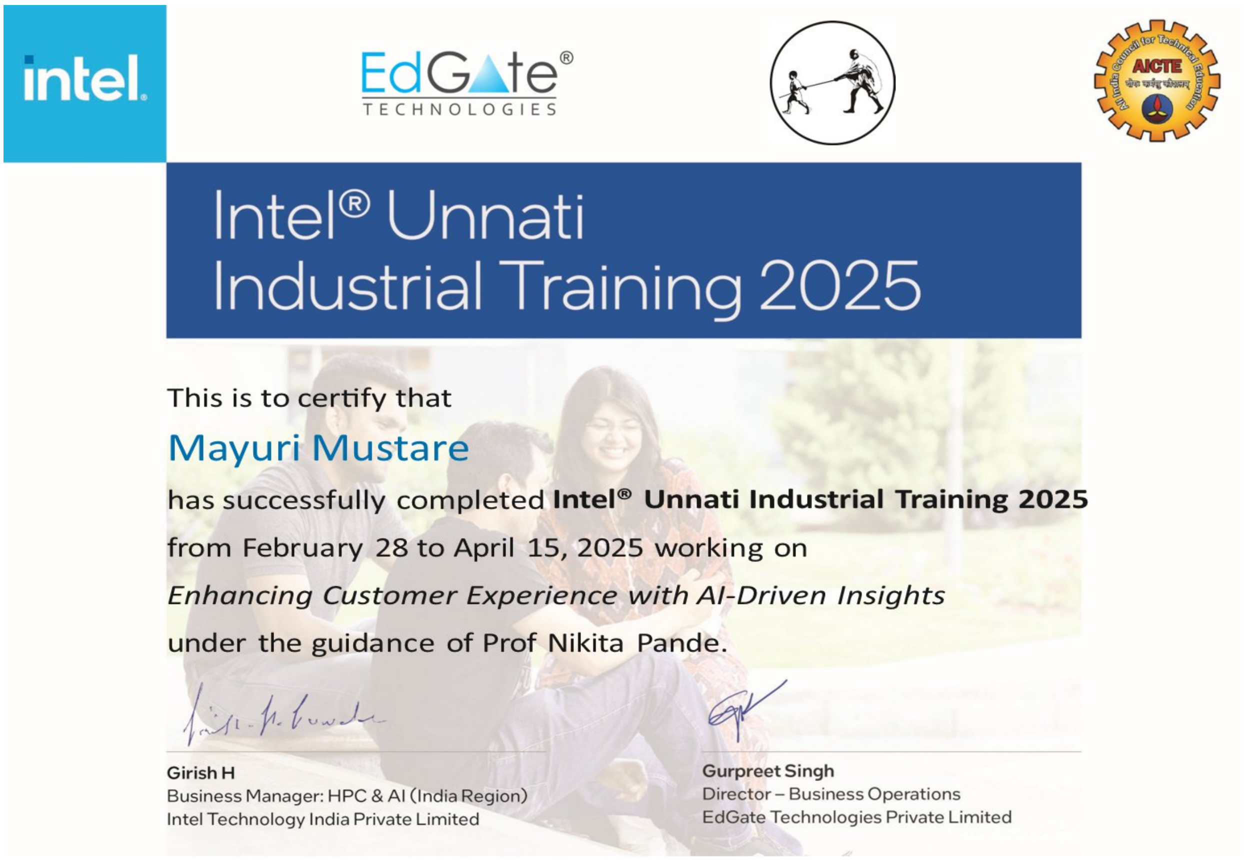

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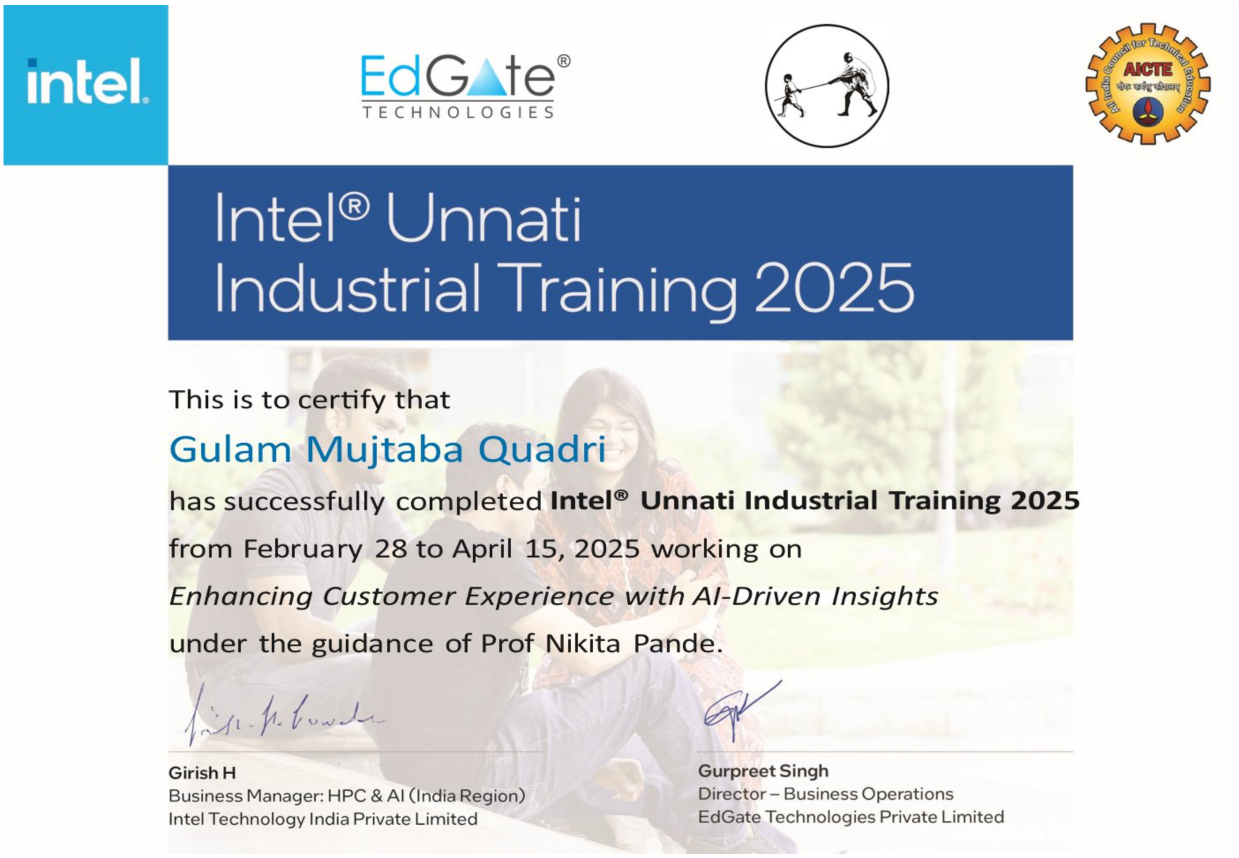

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With Deep Reverence,

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ABSTRACT

“AI-Powered E-Commerce Product Recommendation System”

This project is an intelligent product recommendation and sales visualization system whose backend was done in Streamlit and its frontend interactive charts with Chart.js. The objective of this project is to allow users to explore trending items and customize recommendations to be provided based on previous purchases done by the user. It utilizes two datasets, DMart.csv which contains details of the product such as name, category, and popularity, and Purchases.csv which contains user purchase history.

A recommendation system based on collaborative filtering techniques was implemented to help achieve this goal. This system monitors purchase activity patterns and suggests additional items associated with the selected dropdown entry for the user. The recommendation logic is developed in intel_m.ipynb while the frontend was done using HTML, CSS, JavaScript, and Streamlit. The trending product chart was created using Chart.js which captures the value of various products in the market using a horizontal bar graph thus providing a glimpse view to the users on which products are in great demand.

Users can interact dynamically with the product data using the interface and get instant feedback from the chart and recommendation engine. The sales chart shows specific popularity metrics when the cursor hovers over it. Such interaction allows users to respond better as they adapt to the real-time changes. Moreover, there is also an 'Add to Cart' option in the interface which updates the cart total upon selection, providing an instantaneous e-commerce environment.

This is a good example of how several different technologies can be integrated into one single robust, scalable, and aesthetically pleasing product recommendation system. Data can easily be manipulated in Python, web deployment can be done using Streamlit, and JavaScript can be used for sophisticated charting, making the application fluid and agile. It serves the purpose of students, developers, or even companies interested in tracking user interactions to recommend products and provide data visualization.

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Chapter 1

Introduction

The emergence and growth of digital commerce have changed how products are searched, compared, and bought. Due to the availability of millions of users and online products, sophisticated recommendation systems have become crucial for user guidance. These systems customize recommendations by analyzing user actions, preferences, and characteristics of the products on offer.

This project aims at designing and implementing a hybrid recommendation engine using a real-life DMart inspired e-commerce dataset which is the AI Powered E-Commerce Product Recommendation System. The engine incorporates content-based filtering (driven by product metadata) and demographic collaborative filtering (leveraging age and gender) in order to give accurate customized recommendations.

For model deployment purposes, the system is implemented as a web app using Flask. Interactively, users can input their username or a product, and receive real-time personalized product suggestions. This system is fueled by three core datasets, which include: user demographic data (user_data.csv), product catalog metadata (DMart.csv), and user-product purchase history (purchases_user_product_data.csv).

1.1 Overview of Recommendation Systems

Recommendation systems are a class of sophisticated software capable of filtering data and suggesting items based on a user's anticipated interests or purchasing behavior. These systems are now commonplace in e-commerce, social media, streaming services, and even educational platforms.

A recommendation system can be considered as a special type of an information filtering system which aims to guess the preference or the rating that a user would assign to an item. These systems intelligently recommend products and services to customers as one of the best user-smoothed interface in the era of information overload that seeks to assist users with huge number of choices in such areas like e-commerce, entertainment, education, and social media. The three main types of recommendation systems are:

- **Content-Based Filtering:**
  Looks for items that are similar to those a user has already liked by comparing the item's features.
- **Collaborative Filtering:**
  Looks for users with similar tastes and recommends items that they have liked.
- **Hybrid Filtering:**
  A combination of the both methods in order to deal with issues such as cold-start problems and over-specialization.

In our system we use:

- **Product features:** (Name, Brand, Description, etc.) for TF-IDID recommendations to suggest similar items.
- **User demographics:** (Age ±5, Gender) to cluster users and filter popular items among peers in the same cluster.

All of these approaches work together to achieve a balanced and less monotonous recommendation system.

1.2 Types of Recommendation Systems

Recommendation systems can be classified as follows:

1.2.1 Content Based Filtering:

This is the type of recommendation system where we deal with textual data. Each product

comes with a few attributes like its:

- Name
- Brand
- Category
- Sub Category
- Description
- Bread Crumbs

In this project, we build a "soup" of a string that contains all of the information around a product including the head and tail of the product.

1.2.2 Collaborative Filtering:

The focus of this method is users not items:

- User-based Collaborative Filtering: Recommends what users with similar tastes have liked.
- Item-based Collaborative Filtering: Recommend items that are often liked together.

In our system, we apply demographic collaborative filtering and classify users by gender and age with a 5 year plus/minus range. From this cluster, the system suggests products that are most commonly purchased (excluding items purchased by the user already) to the target user.

1.2.3 Demographic Filtering:

This is an extension of collaborative filtering that uses predefined attributes of a user like age and sex or position. Works well with new users who haven't interacted with the system yet.

1.2.4 Hybrid Filtering:

Used when more accurate results are needed. This combines content-based and collaborative methods.

Each individual method's shortcomings are mitigated, providing backup plans for when user history is insufficient.

Our system alternates between content and collaborative filtering depending on the input type: product or user. This creates a balanced and flexible hybrid engine.

1.3 The Role of Recommendation Systems in E-Commerce

These systems are important in e-commerce since they have a direct influence on sales, customer satisfaction, and loyalty. Their importance is summarized as follows:

- **Improved User Experience:**
  Recommendations continue to engage users, make scrolling uncomplicated, and alleviate the manual searching nuisance.
- **Increased Conversion Rates:**
  Relevant product suggestions remarkably improve the chances of a user making a purchase, which often leads to upsells and cross-sells.
- **Customer Retention:**
  Users are likely to come back especially when their previous visits to the site are remembered and suggestions are tailored to their interests.
- **Efficient Inventory Management:**
  Retailers can use recommendation systems to draw attention to weak sellers or market bestsellers in targeted user segments.
- **Competitive Advantage:**
  The highly personalized recommendation engines of e-commerce leaders like Amazon, Flipkart, and Netflix have propelled them to the top. They serve as our motivation to try emulate these systems on a small scale to demonstrate that even with little resources, impactful insights can be provided.

1.4 Challenges Faced

In constructing an e-commerce AI recommendation engine, several unique technical and conceptual issues arose. [4] While the system is operational and serves its purpose, these challenges shaped the dependability and accuracy of the system.

- **Data Integration Complexity**
  The hardest task was merging three datasets of user demographics, product metadata, and purchase history into a cohesive model ready format. Formatting differences, several missing data points, and nested purchase lists needed a lot of preprocessing in Python with Pandas.

- **Data Sparsity**

  In collaborative filtering techniques, user-item interaction matrices usually have sparse features, especially when the user/item population is large while interactions are few. In an attempt to alleviate this issue, demographic collaborative filtering was employed, using age and gender to build user profiles without needing much interaction data.
- **Cold-Start Problem**

  Traditional recommendation systems find it particularly difficult to deal with users or products that lack historical interactions, referred to as cold-start scenarios. Our hybrid approach addresses such issues with the following:
  - New products are filtered using content-based techniques.
  - New users are filtered using demographic techniques.

  This ensures that useful outputs are provided regardless of available interaction history.

1.5 Project Scope

The project scope covers the entire process from building a working hybrid recommendation engine to making it usable in the real world with a visually appealing and responsive web application. The system demonstrates not only the educational principles of recommendation systems, but also imitates real-world applications of retail businesses.

1.5.1 Functionality Scope

A. Recommendation Models:

- Content-based filtering: returns similar products to the user's selection.
- Collaborative filtering: suggests products to the user based on similarity from demographic information.
- Category-based search: identifies related products based on name (levenshtein) and category matching.

B. Data Handling:

- Uses structured structured tabular data from CSV files, making it fast to load and process offline.
- Supports merging, filtering and transforming sequences of data using Pandas.
- Applies TF-IDF text vectorization and uses cosine similarity similarity to measure distance.

C. User Interface:

- Provides a very basic clean, two column HTML page layout with dropdowns and dynamic lists.
- Allows the user to view Product details, view recommendations, and change between user based and product-based recommendations.

1.6 Objective of the Project

The objective of the system "AI Powered E-Commerce Product Recommendation System" is to design hybrid, intelligent, and web-enabled recommendation systems which propose pertinent products to users in DMart-like settings and environments.

- **Primary Objectives:**
  - Construct content-based recommendation model by employing product metadata and TF-IDF.
  - Create demographic-based collaborative filter using age and gender.
  - Combine three practical datasets: user data, product catalog, and purchase history.
  - Design a web interface using Flask which is capable of supporting interactive recommendations.
  - Allow detailed views of products to be accessed through dynamic linking.
- **Additional Objectives:**
  - Resolve the cold-start demographic issue.
  - Reduce recommendation diversity and coverage problems through the hybrids of two models.
  - Leave the system with a modular and extendable codebase, permitting further such as:
  - Recommendations via chatbots
  - Integration of product rating systems
  - Deploying on the cloud (Heroku, Railway)
  - Re-ranking based on user feedback

In the project, we aim to show how machine learning can be implemented with diverse practical e-commerce cases. Even with scant amounts of user data and product metadata, efficient, personalized, and scalable product suggestions can be developed.

1.7 Summary

The AI Powered E-Commerce Product Recommendation System creates customized product recommendations using a hybrid approach of content-based filtering and demographic filtering. It utilizes metadata about the product, and a user's information like age and gender to provide the best-fitting recommendations without the need to track a consumer's behavior. The introduction explains the purpose of the system and its advantages to the improvement of user experience in the world of e-commerce. The following main chapters report research information, system design, implementation and testing; all detailing how the system was built, how it works and how it performs in real use case scenarios, as well as demonstrating its value as a practical tool for e-commerce and a product for learning purposes.

Chapter 2

Literature Survey

This chapter summarises the existing recommendation system methods so far, as seen through the key distinction of content-based filtering, collaborative filtering and hybrid methods. Content-based filtering is based solely upon product metadata (product name, brand, product description etc.) whereas collaborative filtering relies upon user patterns of interaction and relatedness of users or demographics. Hybrid methods combine both content-based and collaborative filtering to reach the best of both worlds increased accuracy through more data, and decent limitations to cold-start and sparsity.

Within the project we will be using a switching hybrid model where the recommendation system uses content-based filtering logic when the user selections a product or product category, and uses demographic collaborative filtering logic when the user has selected a user or demographic group. Further, the project reflects the recent trend of utilizing frameworks to combine logic into a real-time Flask web application, in keeping with the modern accessible deployable solutions.

2.1 Traditional Recommendation Techniques

Recommendation systems began as rule-based systems reliant on knowledge-manual curation based logic of rules or heuristics. As a result of this manual approach the knowledge base could not adaptor was slow to adapt to shifts in user preferences or the experience was largely frozen when the catalog of products expanded dramatically [1].

A significant transformation occurred with the introduction of collaborative filtering in the early 1990's. The projects Tapestry (1992) and Group Lens (1994) were the first to incorporate automated recommendation systems that leveraged user behavior of participation - ratings, comments etc. - into the recommendation of relevant items. These systems operated using user-item matrices and prepared for distance metrics (using similar measures such as Pearson correlation or cosine similarity) between users or items to determine similar recommendations for users.

Nonetheless, collaborative filtering has its drawbacks:

- It needs enough user data (cold-start issue).
- It fails with sparse user-item matrices.
- It has no concept of item content similarity (why two items might be similar).

To remedy these downsides, the field of content-based filtering emerged. Rather than using user behavior, content-based filtering makes suggestions based on the items attributes. Take this project again for example, content-based filtering works using TF-IDF (based on metadata such as name, brand and description) as opposed to user behavior.

2.2 Content-based Filtering

Content-based filtering is founded on the idea that users will gravitate to item with similar characteristics to those they have liked before. Item characteristics are expressed in feature vectors (keywords and categories) and their vectors are compared for similarity in recommendations.

In the academic literature, one of the more widely used approaches to convert unstructured text to numerical vector is TF-IDF (Term Frequency–Inverse Document Frequency). TF-IDF is a weighting system trying to maximize the rare but important words and minimize frequent but less informative words.

Once the product attributes are in vector form and the dimensions are reduced to be compared, corresponding objects in sparse matrices are often calculated based on their cosine similarity. [1] For example, if a user has liked a shampoo tagged "herbal" and "anti-dandruff," the recommender system will find other products with as high cosine similarity to the other item's TF-IDF vector.

Your project uses the concept in the following way:

- You create a "soup" of metadata (Name, Brand, Category, SubCategory, Description, BreadCrumbs).
- You turn it all into vectors using TfidfVectorizer from scikit-learn.
- You calculate the similarity of products using cosine_similarity
- This allows powerful recommendations to be made based on item descriptions entirely which is a great advantage for new users and new use cases, otherwise known as cold-start situations!

2.3 Collaborative Filtering

Collaborative filtering is the idea that similar users will like the same items. Collaborative filtering does not require item attributes, only user behavior.

Two methods of collaborative filtering in the literature are:

- User-Based Collaborative Filtering: Identify users that are similar to the target user and recommend items that they liked.
- Item-Based Collaborative Filtering: Identify items that are liked together and recommend them to the user.

Classic implementations of collaborative filtering are either k-Nearest Neighbors (k-NN), or matrix factorization and singular value decomposition (SVD).

Probably the biggest contribution to research in collaborative filtering comes from the 2006 Netflix Prize competition that pioneered innovative research in matrix factorization and latent feature models.

In your project, collaborative filtering is done in a demographic-based way:

- This does not use ratings however it groups users according to their age and gender.

- The products are recommend based on what is frequently purchased based on the same demographic group.
- This variation helps to solve cold-start for new users with no purchase history.

This is simplistic collaborative filter that works quite good with sparsely populated datasets.

2.4 Hybrid Filtering Models

Hybrid recommendation model is simply a combination of relevant aspects of content-based and collaborative filtering. The hybrid systems may offer recommendations in various fashions (Burke, 2002).

- Weighted: Result combines scores from both models.
- Switching: Must select on which approach to use based on the user, the user data available or product data will decide which will be used.
- Mixed: The system can offer recommendations from both systems.
- Feature Combination: Aggregate features users and items into one model.

Burke (2002) found that hybrid models increase:

- Coverage (fewer items get go unconsidered),
- Accuracy (more appropriateness of suggestions)
- Robustness (less sensitivity to sparsity of data or cold-starts).

Your project therefore is a switching hybrid model.

- If User Name is chosen, the recommendations will be collaborative filtering.
- If Product Name is chosen, the system will perform content similarity calculations.
- If using a related category search, a fuzzy text search will be performed.

The outcome is a flexible and intelligent recommendation system that can adapt to whatever relevant input exists from user behaviors or metadata.

2.5 Web-Based Recommender Systems and Contemporary Directions

In their early iterations recommender systems were traditionally offline and delivered recommendations in bulk. Now, we have discover services that are seamlessly web-integrated systems, providing real-time recommendations as consumers interact with their web pages.

A number of studies have reported accessibility, usability, and adaptability benefits combining web frameworks such as Flask, Django, and Fast API to rapidly develop and integrate machine learning models in a user's recommender service system. Your recommender service system utilizes Flask's lightweight routing to:

- Accept user data input via form / button submissions.
- Pass user and product data to a processor in the backend engine to process.
- Use Jinja2 templates to dynamically display recommendations by selecting user products.

The merging of front-end (HTML / CSS) content with back-end functions (Python / Flask) allows for a more streamlined and consistently designed experience. The embedded features provided in your recommender service systems produced the following user interface enhancements:

- Persistent dropdown selection.
- Linking users to individual product detail pages.
- Hoverable recommendation lists with dynamic live updates of recommendations.

These embedded features are well documented in Human Computer Interaction (HCI) literature regarding engagement, trust, or click-throughs. Your recommender service also utilized:

- Error handling functionality used when a user or product matched exiting consumer or product listed for a product being recommended to a user,
- Dynamic use of the offline social recommender finding and displaying matches in Google search presented the user list which can be interchanged separated and determined from data list presented, with fully page reload, and readily ran in the background.

Employing these functionalities are in good step with modern user experiences (UX) expected from contemporary AI-based platforms.

2.6 The Real-World Application of Demographic Filtering

Demographic filtering is a type of recommendation that uses demographic characteristics of a user like age, gender, and geographic location to make relevant recommendations. This differs from behavioral-based methods, as demographic filtering does not use any information from the past interaction history to base the recommendation on, therefore it can be useful in a cold-start scenario [6]. Demographic filtering will be an effective solution where some conditions exist such as: the site has just launched; user activity is limited; or, compliance factors restrict the collection of a user's behavioral data. Essentially, demographic filtering allows the system to infer some level of personalization immediately based on only using available data about demographic attributes to guarantee a base level of relevance, the first time a user interacts on the system.

In the example outlined by this system, demographic filtering was used by creating user cohorts of users with similar characteristics; specifically by those who are ±5 years of each other in age, and same gender. This design assumes that many users within the same demographic cluster have some overlap in preferences and shopping habits. To illustrate, a user age of 18–25 will likely have an interest in similar things related to new clothing, gadgets, or personal care products, and this allows the developer to have a lower degree of difficulty recommending attributes that seem popular within that group cohort.

Top-Pros of Demographic Filtering for Real-World Applications:

- Good Handling of Cold-Start Problems: Can still utilize demographic filters to prompt personal recommendations for new users with no prior behaviors.

- Low Privacy Sensitivity: Demographic filters do not rely on behavioral data, which makes it helpful for platforms that limit data collection.
- Easy to Use, and Fast: Demographic filtering doesn't require heavy computational resources like collaborative filtering or deep learning recommendation algorithms, and they are easy to implement and maintain.
- Works Well in Close/Fixed Systems: Demographic filtering is good for settings where various user characteristics are clearly defined, such as in retail chains, an education platform, or subscription service.
- Supplements Hybrid Systems: Demographic filtering is great at enhancing content-based filtering when they are combined together to create more options for diversity and explanation in recommendations.

2.7 Benefits of Hybrid Recommendation Systems

Hybrid recommendation systems combine more than one filtering method, such as content- and item-based filtering and collaborative filtering, to provide recommendations that are more accurate and more robust. This project uses a hybrid recommendation system in order to provide results that are relevant to the user ("user-contextualized") and flexible using a limited amount of inputs.

Benefits:

- Greater Accuracy: Combines item similarities plus group-based behavior of users to provide more relevance in recommendations.
- Cold-Start Mitigation: Can make recommendations for new users and new products based on demographic data and the product metadata alone.
- Better Coverage: If either filtering method (e.g., behavior-based filtering) does not have enough data, personalized recommendations can still be produced.
- Explainability: Increases transparency of recommendation explanations based on the item content versus group-based behavior.
- Greater Robustness: Reduces reliance on a single data source to operate suggesting the system is more stable and robust.

2.8 Relevance for Educational and Industry Purposes

This project has both educational and commercial applications; on the educational side, it can help and guide students who are just beginning machine learning and web deployment; and on the commercial side, it stands as an example for companies looking for inexpensive recommendation options. The project illustrates the use of AI in a real setting and used accessible and open-source software.

Uses and Consequences:

- **Educational Use:**
    - Helps students understand the AI work-flow from uploading a data set to deploying a model.
    - Promotes project-based learning with real tools such as Flask, Pandas and Scikit-learn.
- **Commercial Use:**
    - Provides a scaling and lightweight model for small and medium eCommerce sites.
    - Can be adjusted to work with a variety of products; in this case groceries, clothing and electronics.
    - Provides a less expensive and less complicated way to deploy a recommendation system versus enterprise solutions.

2.9 Research Gap and Project Motivation

While there are ample studies on large-scale recommendation systems commonly used by many platforms, there is a gap in building lightweight, domain-specific and scalable hybrid recommendation systems for small and medium business applications[4]. Most academic solutions often utilize high-dimensional data and require user ratings or deep learning approaches not readily available to retailers with limited resources. This project, therefore, addressed this gap by using structured retail-specific data (similar to DMart), and implementing a hybrid recommendation using both demographic filtering and content-based logic to make good recommendations with the ability to scale without requiring huge infrastructure.

Your project fulfills that gap via:

- Utilization of actual retail mannered and shaped data (in the DMart format).
- Minding to develop behavioral modelling driven metadata items alongside demographic logic.
- Implementing a useable Flask-enabled UI to deploy.
- Multiple variations for recommendations (user-adapted, product based and category based).

2.10 Summary

In Chapter 2, we examined the main techniques used in recommender systems: content-based, collaborative, demographic, and hybrid methods. We covered their pros and cons and identified a gap in the research literature regarding simple, scalable models targeted at smaller platforms. We also explained the motivation behind this project to address that gap, and we intended to do so using real data and a hybrid method of combining content-based and collaborative recommendations. The next chapters describe our process in designing, building, and later evaluating the recommender system. We will cover data wrangling, engineering and implementation of algorithms, deployment on the web, and evaluation of the performance of the system.

Chapter 3

Methodology

The AI Powered E-Commerce Product Recommendation System was developed and implemented using a hybrid approach that utilizes content-based and demographic collaborative filtering. This is a comprehensive overview of all technical and logic flow from obtaining and cleaning data from DMart, through the design of the model, and finally deploying it. The objective was to create a scalable and real-time recommendation engine from structured product metadata and basic demographic user data without relying on any user long-term behavioral tracking or rating history.

The project implemented datasets similar to the DMart retail data, which includes user profiles, product catalog, and purchase history. The pipeline design function including data cleaning, feature engineering, training the model, generating similarity scoring and finally deploying the model as a web app, was all done using programming in Python and using libraries such as Pandas, Scikit-learn, and Flask. The model was deployed using Flask to deliver an operational web server that displays a fully functioning user interface which a user can interact with to receive product recommendations in a real-time application.

File Name	**Description**	**Key Columns**	**Purpose in System**
user_data.csv	Contains information about users including identity and demographics.	User ID Name Age Gender	Used for demograp hic-based filtering.
purchases_user_product_data.csv	Maps each user to a list of product IDs they have purchased.	User ID, Purchased Products	Exploded to enable individual product mapping.
DMart.csv	Contains complete metadata about each product listed on the ecommerce platform.	Product ID Name Brand Category Sub-Category Description Price Discounted Price Quantity Breadcrumbs	Used for content-based filtering and detail view.

Table.01 Overview of Project Datasets

3.1 Methodology Diagram

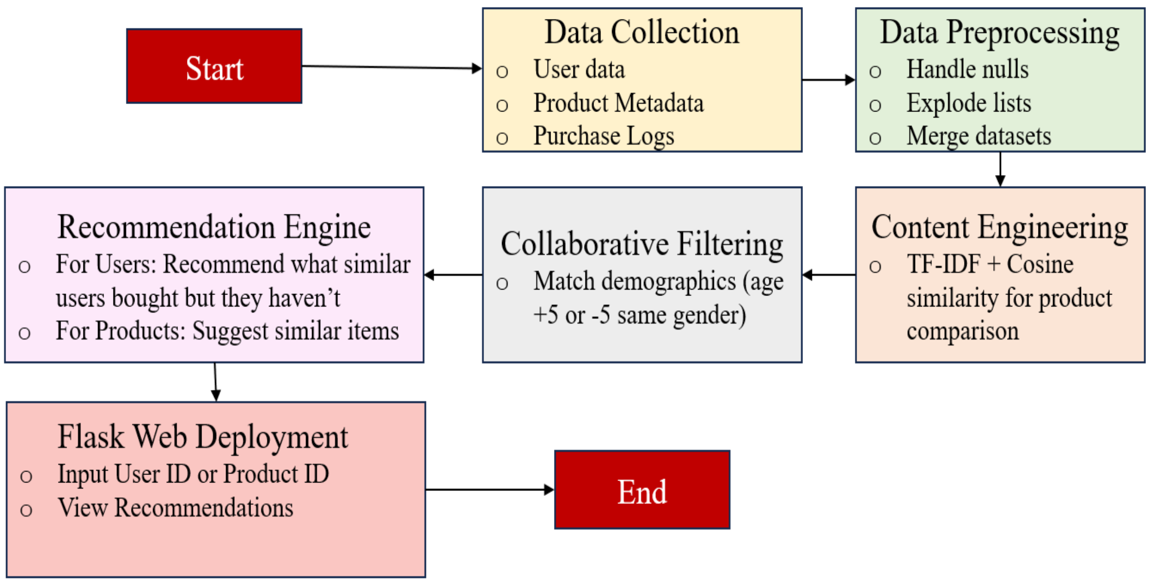


Fig. 3. 1. Methodology Diagram

The architecture of the system flows in a certain direction, with data collection as the starting point from the user, product, and the purchases CSV files. Upon collection, the data is pre-processed and cleaned, removing null values, exploding the lists where appropriate, and merging the datasets, and then processed in two streams, content engineering and collaborative filtering.

The content recommendations were created using TF-IDF and cosine similarity, while collaborative filtering clusters the users by age and gender to suggest popular items as shown in Fig 3.1 both methods produce results that feed into a recommendation engine, which returns results in real-time using a Flask-based web application to present personalized recommendations and to maintain a seamless user-experience.

3.2 Dataset Description and Preprocessing

Any recommendation system can only be as good as the data it is based off of and how well that data is structured. In this case three CSV files are the pure data source:

- user_data.csv: Contains basic user demographics. User ID, Name, Age, Gender. For demographic based collaborative filtering, demographic features are important.
- purchases_user_product_data.csv: Contains information on what users purchased. Each row contains one user ID and a string of comma separated product IDs.
- DMart.csv: Contains information about each product, including Product ID, Name, Brand, Category, Subcategory, Description, Quantity, Price, Discounted Price, and Breadcrumbs. Since this is a grocery and pharmacy preserves in one place (similar to the combined format of Walmart), many products were placed in multiple relevant subcategories that it fits under no one category.

3.2.1 Preprocessing Steps:

- Processing Null Values - All null values, especially important ones such as product meta data will be filled with null identifiers. This will consistently guide the models by ensuring there are levels they would understand.
- Purchases Explode - The purchases data has a single column (that contains the product IDs) in a string format is exploded using the DataFrame method. explode() converting that column from a list of products to rows for merging.
- Data Type Change - Various column data types on the DMart product data were casted into string format (e.g. Product ID) to ensure consistency when merging.
- Data Merging - User, Product, and Purchases data were merged into one DataFrame. This one data set permits the ability to access user demographics and product features from one place.

3.3 Content-Based Filtering

Content-based filtering provides recommendations based on products that are similar to aselected product. This method of recommendation is useful when users are browsing one item and would like to see similar products.

Implementation Steps:

- **Feature Engineering:**
  A composite textual feature, `soup`, is formed by concatenating the Name, Brand, Category, Sub Category, Description, and Breadcrumbs fields. This text is representative of the product as a whole.
- **TF-IDF Vectorizer:**
  The `soup` texts are converted to a TF-IDF matrix using Scikit-learns Tfidf Vectorizer. TF-IDF (Term Frequency-Inverse Document Frequency) gives more weight to words that appear infrequently and, therefore are more meaningful. It reduces the weight of words that are common.
- **Cosine Similarity:**
  In order to get a similarity score between each pair of products, the TF-IDF matrix is then passed into the cosine similarity () function.
- **Recommendation Function:**
  Once the user selects a product, retrial the index for that product, ranking every other product by similarity score and returning the top N most similar products.

This filtering method works well for recommending similar brands, direct matching categories, or similar described products. It is especially useful for users looking to compare products or substitute for an alternative.

3.4 Demographic Collaborative Filtering Method

Demographic collaborative filtering provides a means of recommending products based on users' similarities to one another with no explicit behavior or rating data.

How it works:

- **User Grouping:** When selecting a user, the system will determine what other users are in the same gender and +/- 5 years for age.
- **Behavioral Inference:** It assumes that users within a demographic have common needs or preferences; particularly in retail situations.
- **Product Frequency Ranking:** Taking any products other users purchased – excluding those already owned by the target user.
- **Result Filtering:** The remaining products are ranked based on how frequently they appeared in any of the groups' purchase histories. The top results can be returned as the recommendation.

This technique is especially useful when dealing with cold-start users or new accounts with little or no purchase history. This approach works well because the products are located in a structured domain (retail) where one can assume that consumer behavior patterns often vary with age and gender.

3.5 Keyword Matching for Related Product Discovery

In addition to directly similar products or demographics, our system also includes a lightweight way to discover related products based upon name matching [7]. This can enhance exploratory behaviors and reveal product diversity.

How it Works:

- **Keyword extraction:** First the product name is broken int individual keywords, one by one.
- **Matching mechanism:** Next, after parsing the product, the system loops through the dataset to find other product names that share one or more of the same keywords - ignoring capitalization and punctuation.
- **Filtering and ranking:** Once completed, duplicates are removed from the matching results and returned in a list. A filter option to list by category or brand is available.

This technique does not require machine learning models, but is simply a set of string-matching techniques performed in Pandas. While definitely not as robust as TF-IDF models for keywords, it is very quick and good for finding alternatives in a product category or products that are loosely associated.

3.6 Recommendation Logic and Code Organization

All filtering and recommendation logic is in its own script, recommender.py, to simplify the separation of backend activities from the web layer.

Main Functions:

- **get_recommendations(product_id):** Uses TF-IDF and cosine similarity to provide content-based recommendations.
- **recommend_for_user(user_id):** Uses demographic filtering to determine popular products among similar users.
- **predict_related_products(product_name):** Uses exact keyword matching to suggest related products by name.

The modular format of the code allows each recommendation strategy to be maintained, tested or updated independently. Additionally, developers can easily insert new algorithms or data sources without needing to affect every part of the system.

3.7 Web Deployment with Flask

The final system is made interactive and accessible through a Flask web application. Flask is helpful for routing, processing input and rendering output.

Key routes:

- / - loads the home page with dropdown forms for user/product selections.
- /recommend_user - retrieves recommendations based on demographic data.
- /recommend_product - retrieves content-based related items.
- /related_category – retrieves Products that are related by keyword.
- /details/ <product_id> - displays detailed product metadata.

Flask uses Jinja2 templates to dynamically inject data returned by Python into HTML pages. The architecture represents a real-time experience as users navigate recommendations and choose product details.

3.8 User Interface and User Experience

The system's UI has been designed with usability and performance in mind. The UI is built with HTML, CSS, and Jinja2, and the following usability features are included in the UI:

- **Grid Layout:** A layout using a two-column grid distinguishes the input (user/product selection) from the output (recommendations) by assigning one full column of space to display the input and providing a distinct column to display the output.
- **Styled Input Forms and Buttons:** The CSS styling of the input forms and buttons further communicates visual clarity and feedback to user interactions.
- **Dynamic Interactions:** When users submit the form, the results of their recommendations seamlessly updated, without requiring the browser to perform a general page reload.
- **Clickable Products:** Each recommendation provided a hyperlink to the specific product displaying a detailed product page.
- **Retained Form Inputs:** Variables collected from the user input form persisted after a submission to maintain user navigation.

Ultimately, this interface design considers the unique characteristics of different user types so that all users, regardless of technical knowledge or skill level, can effortlessly interact with the system, navigate results of recommendations, and explore additional recommendations related to the recommendations.

3.9 Tools and technologies used

To build and deploy the system, we used the following technologies:

- Python: Programming language for core coding.
- Pandas: To read, clean, transform and merge data.
- Scikit-learn: For TF-IDF vectorization and cosine similarity
- Flask: The web server for routing user input and returning results.
- Jinja2: Used to dynamically render templates.
- HTML/CSS: To create and style the frontend.
- VS Code / Jupyter Notebook: Development environments for writing and testing code.

These are all standard technologies; they're easy to adopt/learn and are appropriate for developing re- time AI-powered web applications.

3.10 Summary

The thesis concentrates on the methodology surrounding recommendation systems that are discussed in Chapter 3. More specifically, this chapter outlines the various processes and my implementation that supported the recommendation engine, which was the analysis of the documents, TF-IDF vectorization (for content-based filtering), implementation of demographic logic (ages and genders). The next chapters provide an explanation of the structure and technologies used to create the system (Chapter 4), an outline of the implementation steps (Chapter 5), and an evaluation of system performance including usability, and accuracy of the recommendation system in terms of testing and analysis of result approaches (Chapter 6).

Chapter 4

System Analysis

System analysis entails a detailed examination of how a software system is configured and working to fulfill its intended objectives. It is an inspired decomposition of the components of the system such as system architecture, data flow, input and outputs, and logic design. System analysis is essential for this AI Powered E-Commerce Product Recommendation System because it offers assurance that the hybrid recommendation process, the architectural design, and the real-time responsiveness are all working as intended.

System analysis will determine whether the developed software solution not only works but also meets user expectations for performance, and scalability, as well as user experience. Each part of the system, from data ingest to web interaction, has been analysed as an individual element as well as part of a unified pipeline to validate that their operations will be consistent and extensible in the future to allow for value added operations.

4.1 Problem Identification

In contemporary e-commerce, users are often confronted with information overload. In an environment where thousands of items are listed in various categories, it can be hard to discover relevant items. Filtering tools that previously existed such as categorically filtering and manually sorting items do not personalize the user interface nor have limited success. Furthermore, there are recommendation systems available in the market but they are largely disadvantaged and targeted toward larger enterprises with complicated behavioral tracking. Small businesses would be unable to utilize these systems.

A particular challenge is presented by cold-start users (users without a previous transaction history) and cold-start products (a new product in the database where there are no previous interactions) whereby traditional collaborative filtering mechanisms fall short [3]. While data protectionist budget restraints and data protection issues preclude small businesses from developing sophisticated AI systems. In this project we identify these pain points and provide a hybrid model using rudimentary structured metadata and demographics to assist in providing useful product recommendations, and avoids the necessity for a decidedly higher degree of behavioral tracking normally associated with large enterprise behavioral metrics.

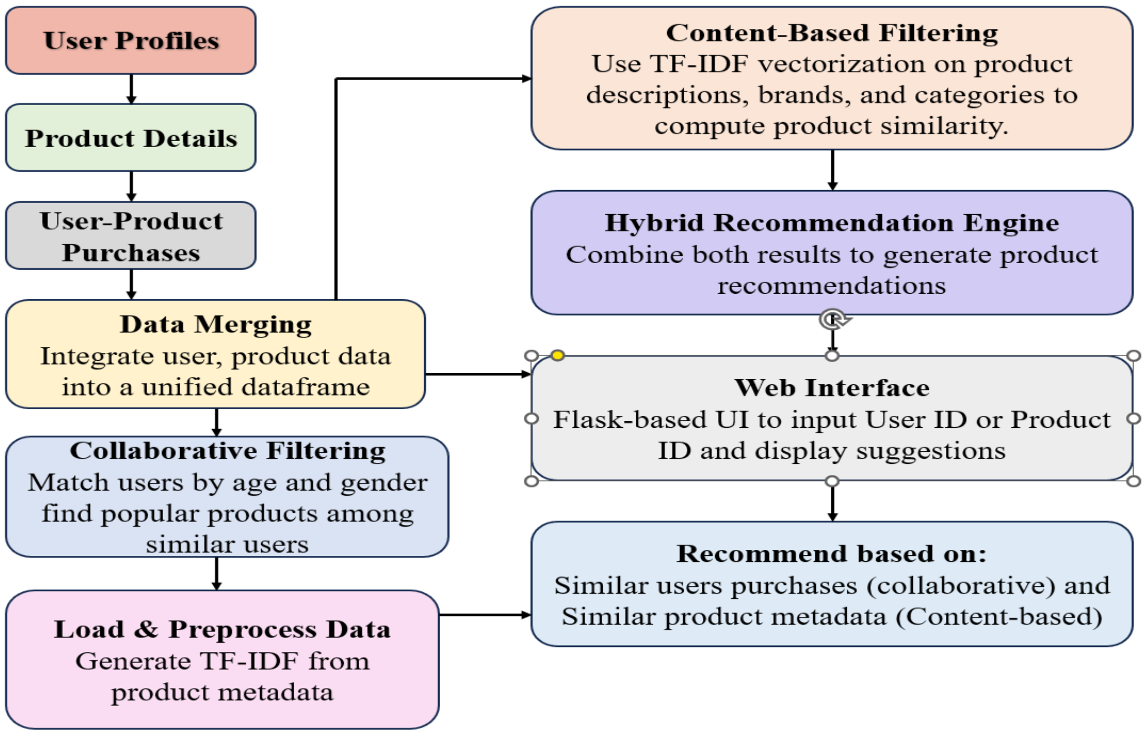
4.2 System Objectives

Users have an issue with information overload in today's e-commerce landscape. Thousands of products exist in several different categories and it's often too difficult to find anything useful. Current filtering tools (searching by category, and manual sorts like sorting by price and popularity) do not sufficiently personalize the user experience. Additionally, when many users interact with the product or service providers, those systems were designed for large enterprises. Generally speaking, interaction tracking can be difficult to perform for small entities.

There are unique context-driven situations that arise related to cold-start users (users with no purchase history) and cold-start products (a newly added product with no user interactions), independently or jointly, where contextual or collaborative filtering fails as solutions. Limitations in metrics and issues in data compliance often create challenges for small businesses, such as budget and data privacy limitations, that can prevent adequate utilization of highly robust AI systems [2]. This project identifies the pain points above and proposes a hybrid model that uses basic structured metadata along with demographic to provide meaningful product suggestions while minimizing large-scale behavioral or interaction tracking.

4.3 System Architecture

The system architecture for the AI Powered E-Commerce Product Recommendation System is modular with the main focus for efficiently managing user requests, processing user data, providing intelligent recommendations based on user behavior, and deploying the results to end-users through a web interface, developed in Flask as shown in Fig. 4. 3 The architecture follows a logical and linear flow from data sources to final product recommendation.



User Profiles
Product Details
User-Product Purchases
Data Merging
Integrate user, product data into a unified dataframe
Collaborative Filtering
Match users by age and gender find popular products among similar users
Load & Preprocess Data
Generate TF-IDF from product metadata
Content-Based Filtering
Use TF-IDF vectorization on product descriptions, brands, and categories to compute product similarity.
Hybrid Recommendation Engine
Combine both results to generate product recommendations
Web Interface
Flask-based UI to input User ID or Product ID and display suggestions
Recommend based on:
Similar users purchases (collaborative) and Similar product metadata (Content-based)

Fig. 4. 3. System Architecture

4.3.1 Data Sources

- **User Profiles:** The user profiles include user information such as name, age, and gender, available from user_data.csv. The reason for using these attributes is for demographic filtering; in particular grouping users by age (±5 years) and same gender.
- **Product details:** Product details are available from DMart.csv. This file contains a product of metadata (name, brand, category, description and pricing). These are used to create a TF-IDF vector to determine content-derived similarity.

- **User- Product Purchases:** Purchase history is available from purchases_user_product_data.csv. It shows which user bought which products, but it is used more to model user behavior indirectly.

4.3.2 Data Merging

The first critical backend step is merging the datasets into a single DataFrame. Each user has their products they purchased mapped to them, and each product is wrapped with metadata. This unified data view is a necessity for executing both recommendation algorithm types = content-based and collaborative.

4.3.3 Load & Preprocess Data

Data can only be recommended after it has been cleaned and prepared for further actions.

- Nulls in the product metadata will need to be filled.
- The product metadata fields will need to be concatenated together to form a composite "soup" for text analysis.
- A TF-IDF vectorizer will be applied to that soup so that similarity can be computed.

This step helps ensure uniformity of data and seeded for quicker execution and model building.

4.3.4 Collaborative Filtering

This module handles demographic-based collaborative filtering:

- Other users that match the user's gender and are within a +/-5-year age range are filtered for the selected user.
- The products purchased by those users will be logged.
- Items purchased by the selected user will be filtered out.
- The remaining products that have not been filtered out will be ranked by frequency and recommended.

This model allows users to receive relevant recommendations and does not need explicit ratings or length of use or behavioral history.

4.3.5 Content-Based Filtering

Similar to collaborative filtering, this step determines product-to-product similarity:

- The TF-IDF matrix from pre-processing is referenced here.
- The cosine similarity is calculated between the selected product and all other products.
- The top-N similar products are gathered and output. This works best in scenarios where a user is on a page and wants suggestions for related selling items.

4.3.6 Hybrid Recommendation Engine

Both types of recommendations (content-based and collaborative) are unified under a hybrid logic engine [5]. Depending on the input type (User ID or Product Name), the system either routes the request to their respective algorithm, or aggregates results if needed. To combine these algorithms is to improve accuracies and address common problems like cold-start.

4.3.7 Website Interface (Flask Layer)

The website interface is constructed as a Flask App with Jinja2, which:

- Accepts user inputs via dropdown forms.
- Invokes respective backend functions, and
- Displays some dynamically generated recommendations in a user-friendly list format. Each result includes a clickable title to a detail view, with all relevant product information.

4.3.8 Final Recommendation Output

At the end of the flow, users are provided with recommendations directly for products:

- Collaboratively filtered from products purchased by similar users, or
- Content-based filtered from products which are similarly textually represented in the metadata.

4.4 System Goals

The aforementioned recommendation system was built with specific goals in mind, and those goals were realistic in scope, meant to directly address a real-world problem, and to be light and easy valued implementation:

- Provide real-time product recommendations via a hybrid approach that used a combination of content-based filtering and demographic filtering.
- Not rely on ratings history or behavioral information so that it was applicable for any sort of cold-start scenario.
- Be modularly designed so that the logic, data and presentation were kept separate, and any component could be separately debugged and/or scaled.
- Have a user-friendly interface that is simple and direct with very few steps required to interact with and generate a set of recommendations.
- Be deployable for educational and small business use, and maintain the belief that the end-user should be able to understand, use and extend the system without advanced technical understanding.
- Be flexible to allow the integration of additional features such as feedback loops, behavior tracking, or recommendations based on an NLP-enhanced strategy.

These goals were made use of to drive dimensions regarding the technical design of the system and the decisions surrounding the functionality of the system.

4.5 System Architecture Overview

The system has a 3-layer architecture that separates all related functions within the system.

4.5.1 Data layer

The data layer is created using static CSV files in the following format.

- user_data.csv - Contains user profiles with age and gender.
- purchases_user_product_data.csv - Contains the user to purchased product ID mappings.
- DMart.csv - Contains product metadata with name, brand, category, sub-category, price and description.

A Pandas library loads all the files into DataFrames for the default input.

4.5.2 Logic layer

The logic layer includes the Python functions located in recommender.py, it contains the recommendation algorithms, the processes happen any time a new HTTP request is sent via user engagement with the presentation layer. It includes:

- TF-IDF vectorization of product metadata
- Cosine similarity calculations
- Demographic filters based on user defining features
- Ability to match key words in relation to each of the products

4.5.3 Presentation layer

The presentation layer instead routes of the Flask web framework has web based outputs such as:

- HTML templates with Jinja2 templating language
- Forms and buttons styled from CSS
- Call routes of different types of recommendation queries

By separating the different layers it provides autonomy to understand the aspects of the system easy and maintenance related to each layer can be done without fuss. For example if there was to be an update to the UI the logic layer would not be impacted; or if some of the dataset updates were modified the code would not have to be changed.

4.6 Data Flow Explanation

The data flow in the system is linear and was implemented now slightly different.

- A user opens the home page and chooses a User Name or Product Name from a dropdown list.
- The user then clicks a button, which creates a POST request which is sent to Flask.
- Flask knows which function to route the request to (recommend_for_user, get_recommendations, or predict_related_products).
- The relevant function will process the user input utilising the preloaded DataFrame and a lesson or output recommendation list.
- The output from the function is sent back to the template to render dynamically to the right of the screen.

The key advantage of this flow is the recommendation workflow can be real time interacting and does not require full page control flow reloading or interacting with an external database. All of the processing is done in-memory allowing the app to respond, in a very fast manner to user actions.

4.7 Input and Output Design

This design minimizes interaction while maximizing value, allowing any user (technically challenged or not) to utilize.

- **Input Design:**
  - Dropdown forms are utilized for input selection by username and product name.
  - Each form also includes a clearly labeled submit button.
  - All inputs are validated in Flask for cases such as a missing entry, or invalid entry.
- **Output Design:**
  - Recommendations appear in a styled list with each product name linking to a more in-depth view (/details/).
  - If no products are suitable, there is a clearly displayed notification such as "Product Not Found".
  - The form state is preserved after submission to minimize the amount of re-selection.

4.8 Algorithm and Logic Design

There are three core algorithms in the system:

- **Content-Based Filtering**
  - A textual feature (soup) is built from product meta-data.
  - The soup is transformed into numeric vectors through TF-IDF vectorization.
  - Cosine similarity is used to calculate the similarities between products.
  - A function returns the most similar N products available to the selected one.
- **Demographic-Based Collaborative Filtering**
  - Users are first filtered by same gender and ±5-year age range;
  - Products purchased by these users are collected.
  - Products already purchased by the target user are filtered out.
  - Recommendations are made on the most common items.
- **Keyword Matching**
  - The selected product name is divided into keywords.
  - Other product names are scanned for matching terms.
  - Results are returned with loose, relevant suggestions.

logic is contained inside separate functions in recommender.py which allows for reuse and ease of testing.

4.9 Technology Stack and Tools Used

This system was designed using open-source, beginner-friendly, and production-ready tools:

4.9.1 Python

Python is the central programming language for the backend logic and system orchestration. Python is easy to use, has a broad ecosystem of libraries, and is flexible; it is a great option to develop an AI-based web application. Python is used in the project for:

- Reading and preprocessing data using Pandas.
- Developing the recommendation logic (e.g. TF-IDF vectorization, cosine similarity, demographic filtering).
- Creating and running the Flask web server that routes user input and serves up the results dynamically.

Python facilitates modular programming, and is widely adopted in the machine learning community, which helps to make the system both powerful and maintainable.

4.9.2 Pandas

Pandas is a powerful data analysis and data manipulation library in Python so broadly used to work with structured data (like CSV files). In this system, Pandas are used to:

- Load datasets (user_data.csv, purchases_user_product_data.csv, DMart.csv) into DataFrames.
- Cleaning and transforming data - i.e. removing null values, exploding lists into rows, merging datasets, and formatting columns.
- Provide additional simple filtering, grouping, and sorting - each of which is important to generate recommendations based on user demographics or product metadata.

Pandas makes working with complex data simple, and simplifies the data to prepare structured datasets that are suited for machine learning pipelines.

4.9.3 Scikit-learn

Scikit-learn is widely regarded as the preeminent machine learning library in the Python ecosystem. It is designed for model building, data transformation, and algorithm evaluation. For this project, Scikit-learn was used for:

- TF-IDF Vectorization: This takes the text data (e.g., product name, description and category) and converts this into numerical vectors, weighing terms that are important and de-noting terms that are common.
- Cosine similarity: This computes the similarity between products, which is the angle between the TF-IDF vectors. This is a critical aspect of the content-based recommendation system.

Scikit-learn abstracts the complexity of many mathematical operations in simple APIs so you can quickly implement and experiment with models.

4.9.4 Flask

Flask is a micro web framework written in Python that is used to create web applications without needing to do a lot of initial setup. It was used in this project, for the following features:

- Define all routes in Flask to handle requests from users for predictions (e.g., /recommend_user, /recommend_product and /related_category).
- Dynamically serve HTML templates using the returned data from backend recommendation logic.
- Capture user form submissions, route requests to a Python function, and return results without requiring a complete reload of the page.

Flask offers the flexibility to create a lightweight, real-time recommendation service, which is especially valuable in educational and prototype development contexts.

4.9.5 Jinja2

Jinja2 is a template engine used with Flask to render HTML pages with dynamic content. It works beautifully with Python variables along with control structures, like loops and conditionals. In our system, we utilize Jinja2 to:

- Place recommended products into our HTML layouts.
- Add user and product arrays to dropdowns dynamically.
- Remember form inputs across submissions, or any error messages to display if appropriate.

With Jinja2, the front end has a life form within it, as we are able to pass data from the Python server side to the HTML pages, without having to use JavaScript frameworks.

4.9.6 HTML & CSS

HTML (HyperText Markup Language) and CSS (Cascading Style Sheets) are the fundamental building blocks for web page structure and presentation. Within this project:

- HTML is responsible for creating the layout of the forms, buttons, dropdowns and lists the user will be interacting with.
- CSS allows for presentation style of those elements using a defined color palette, spacing, hover effects, rounded edges and responsive layout.

Together they establish a user interface that is both functional and designerly consistent with current web design practices.

4.9.7 VS Code and Jupyter Notebook

Both are strong development environments used in the development of this system:

- Visual Studio Code (VS Code) is a code editor. It's used to write Flask routes, HTML and CSS files, and script files such as app.py or recommender.py. It has good syntax highlighting, filters for version control, and offers extensions for Flask and Python.

- Jupyter Notebook is an interactive environment used for exploratory data analysis and testing out machine learning logic. It allows the developers to run Python code in blocks, watch DataFrame outputs visually, and change their logic in separate environments before transferring it to the main project.

Combining the two development environments allows processes in synchronous time and the ability to use exploratory research and undertake backend development more quickly and efficiently.

4.10 Strengths and Limitations of the System

- **Strengths:**
  - Hybrid filtering, overcoming cold-starts, and increasing diversity.
  - No explicit ratings and no behavioral tracking.
  - Very fast (real-time) and computationally light.
  - Uses a modular coding style that is easy to update and add onto.
  - Has a clean and simple user interface that is conducive to user engagement.
- **Limitations:**
  - Does not adapt dynamically and does not learn from user behavior over time.
  - New items need to be manually added to the CSV files.
  - No ability for personalized long-term tracking and session management.
  - Use of keyword matching isn't sophisticated and can sometimes produce loosely relevant products.

The current version is a powerful example of simplicity and could easily be made more sophisticated with feedback loops, user session tracking, or with API access to the product inventory.

4.11 Summary

Chapter 4 emphasized the system analysis, including the architecture, functional elements, tools and technologies utilized in constructing the recommendation system. It described how Python, Pandas, Scikit-learn, and Flask are used together to create a modular, scalable, and efficient recommendation system design. The next several chapters will follow describing the actual steps involved in implementing each portion of the system (chapter 5) and discussing code structure and integration of those portions. Following there is a complete evaluation of the recommendation system based on performance, accuracy and usability utilizing testing articulations and actual user's feedback (chapter 6).

Chapter 5

Design and Implementation

The design and implementation process signifies the conversion of an idea to a real, operational software project. In this case, the development of the AI Powered E-Commerce Product Recommendation System is exceptionally important, as it connects the knowledge of recommendation algorithms with the implementation strategies to create a functioning application which is responsive in real time.

This chapter discusses how multiple technologies and design principles were brought together to develop the system from scratch. We begin with what technologies were chosen, such as Python for processing data and writing algorithms, and Flask as the web-based framework for direct routing and user commands [1]. We emphasized using technologies that were light weight and allowed flexibility and ease of use, should we continue on to other projects, in academia or in the applied world.

The system uses a hybrid recommendation strategy which combines:

- Content based filtering: Analysing product characteristics (product name, brand, description) by way of Term Frequency - Inverse Document Frequency (TF-IDF) and cosine similarity to determine similar products;
- Collaborative filtering using demographic based affect: Group users by age and gender to estimate projections of predicted preferences, even in cases where historical user behavior is absent.

The front-end design of the system focuses on user experience and sufficient real-time feedback. The HTML and CSS are utilized to create a clean and responsive layout, while dynamic personalization of content provided through Jinja2 templating. This allows users to seamlessly interact with the application and select users or products from dropdown menus as the system makes intelligent suggestions without updating the full page.

In addition, the design embraces modularity and clear separation of concern. All the logic is wrapped in separate functions in a separate recommender.py file. Routing and rendering response are handled in app.py, leaving the templates in their own folder; this allows for independent management of the interface and the back-end logic.

In this chapter, we will explain in detail the file structure, the organization of the files, how algorithms are implemented, and how users interact with the files, that underpin the system. We also show how each design choice leads to performance, extensibility, and usability in the system. Whether it is used as an academic demo or by a small business, the system demonstrates how structured data and machine learning can be connected to create intelligent user-driven applications in the e-commerce industry.

5.1 Design Principles and Approach

The design of this recommendation system is based on a number of principles in order to keep developing functionality, usability, and extensibility:

- Modularity: The system is designed as independent components such as data preprocessing, recommendation logic, and user-interface templates. The modular approach allows for the independent upgrading, and if necessary, replacement of components without the impact to other components.
- Scalability: The architecture allows for the addition of new recommendation algorithms to scale, as well, as the ability for larger datasets, such as deep learning, or user-feedback looping, can be added in future versions.
- User-Centered Design: The system design is user-centred, in that it was designed for simplicity, where users can select from dropdowns and immediately get recommendations. A technical background is not required.
- Performance: As the datasets are loaded in memory with Pandas and logic is achieving computational efficiency with vector operations, the time to deliver is very good and real-time.
- MVC Pattern: The system has elements of the MVC design pattern at a loose level, the datasets are the model, the routing in the Flask application is the controller, and the HTML/CSS templates are the view.

These principles helped to shape the correct process for implementation as well as inform decisions about the best way to structure code, how to encode data to move between structural components, and how to provide interactions.

5.2 Data File Structure and Organization

An organized data file structure is important when maintaining a clean and easy to manage project structure. The system relies on three main CSV files in the data/ directory:

- user_data.csv: Contains basic user information (User ID, Name, Age, and Gender). This is the input to filtering by demographic information.
- purchases_user_product_data.csv: Represents the information that provides each user with a list of products they have purchased. This is the pre-processed (exploded) data to be used for recommendation algorithms.
- DMart.csv: Represents the full product catalog (Product ID, Name, Brand, Category, SubCategory, Description, Price, Quantity, and Breadcrumbs).

In addition, the directory structure includes:

- static/style.css: For styling the HTML page(s).
- templates/: Contains the front end files (index.html, results.html, details.html).
- recommender.py: Contains all algorithmic logic.
- app.py: The Flask application that connects everything together.

Maintaining the described directory structure allows for easy access and navigation. It also provides better debugging capabilities and maintains extensibility in the system.

5.3 Front-End Design (HTML/CSS)

The front-end is designed as simply and functionally as possible so that the user can engage with the recommendation system without confusion. These are the main front-end design pieces:

- HTML Forms: There are three dropdown forms—one for user-based recommendations, user-based product recommendations, and user-based to a product category of related products.
- Responsive Grid Layout: The screen is divided into left (web forms) and right (displaying output, recommendations)
- Dynamic Lists: Recommendation output is completable in a scrollable list style with the product name and a link to view more information attached to each product in the list.
- Styling: The front-end interface uses a custom CSS file that has a brand colour palette (greens and beige), added hover animations for buttons and lists, and rounded corners for styling.

All HTML pages are injected with dynamic content through Jinja2 templating such as user names, product names, and lists of recommendation outputs. Jinja2 allows for the elimination of JavaScript for dynamically populating data and works well for deployment.

5.3.1 Responsive Design Layout

The layout uses a CSS grid system to organize the screen in 2 primary panels:

- Left Panel (Main Container): This area displays the input forms where users can make selections.
- Right Panel (Side Container): This area only renders the recommendation results as dynamic lists.

This layout keeps the interface clean and organized no matter what screen size is being used. The response design allows the system to function across various devices, not limited to desktops, tablets, and possibly mobile screens.

5.3.2 Dynamic Lists for Output

The recommendation results will be outputted in an alluring scrollable list format. In each list item the users can see:

- The product name as a clickable hyperlink.
- A link to a product specific page where more information for the product will include brand, category, price, and description.

The list items are designed with hover effects to increase interactivity, and will provide a smooth transition effect during the whole experience. The interface allows users to quickly browse through their recommendations and click on the product to access more details.

5.3.3 Styling with CSS

The system uses a CSS file found in the /static/ directory. The styling follows a brand color palette with earthy colors like:

- Dark green (#243010)
- Olive (#87a330)
- Lime (#a1c349)
- Beige (#cad593)

Additionally:

- The buttons and forms have rounded corners to look more modern.
- There are box shadows to add some depth.
- There are hover animations for buttons and list items to indicate interaction.
- There is clean typography for readability, using a sans-serif font.

These design elements work together to accomplish a visually cohesive and accessible front-end experience.

5.3.4 Dynamic Rendering through Jinja2

All of the .html files use Jinja2 templating to dynamically inject the content user data, product names, and recommendation results into the HTML structure without any JavaScript. Through Jinja2, the backend (Flask) can send user data, names of products, and ecommendations at runtime directly into the HTML layout.

- All of the drop-down options would use a {% for user in users %}, or {% for product in products %} loop in order to populate the drop-down menu options.
- If a user selected something, I would use a {% if results %} block to render what they selected.
- The forms selected by the user persist after submission to provide the user experience for subsequent selections too.

This also helps when developing and each page is a little bit easier to manage and maintain, and therefore keeps the user interface light.

5.3.5 User Experience Focused

The overall user interface is designed to be easy to use and without any cognitive strain:

- No typing, all options are pre-populated, and selection options are very clear.
- The results appear on the same page, meaning that nothing is disrupted, and there is no page reload, or redirection after submission.
- All error messages come through the layout as quickly as possible so users receive immediate feedback.

5.4 Back-end Logic with Flask

Flask is used to respond to web requests, deal with input, call functions within recommender.py, and render templates to output the data returned from those functions.

There are five main application routes in app.py:

- /: Show the homepage and accept input forms.
- /recommend_user: Accept a user name, find their id, and make recommendation based on demographics.
- /recommend_product: Accept a product name and return a list of similar products based on content features.
- /related_category: Suggest related items that match keywords from the product name.
- /details/: Show everything we have about a given product.

Each route includes logic for handling errors, like invalid input, and the logic for the user to advance through the site. The back-end is very lightweight, making use of only basic Python libraries and Scikit-learn for some of the machine learning capabilities.

5.5 Recommendation Logic Functions

The recommendation system's logic functions are the core of the recommendation system, processing either user or product input, and creating and returning intelligent recommendations. These logic functions are located in the recommender.py module, separating core business logic from web routing and server interface [7]. Decoupling logical business functions can provide cleaner, accessible, and reusable code, and allow for scalability in the future.

Each function accepts unique input and applies one recommendation strategy: demographic filtering, content-based similar filtering, and categorical-based filtering, affording users a flexible recommendation process. All functions return Pandas DataFrames, which are then transformed into dictionaries for the Flask front-end, and passed with Jinjaz templates for further transformation and display.

5.5.1 recommend_for_user(user_id)

This function constructs demographic-based collaborative filtering. It is based on demographic clustering and assumes that users that have similar demographic profiles (same gender and moderately similar age) will have similar products preferences. The flow involves:

- Demographic Membership: The function first extracts the age and gender of the input user from the user_data.csv file.
- User Membership: It then finds users who are the same gender and within ±5 years of the input user's age.
- Purchase Membership: For these users that matched the demographic, the function retrieves their purchase history from the purchases_user_product_data.csv file.
- Filtering: The function then filters for those products the input user has already purchased to avoid providing redundant products.
- Ranking: The function will group and rank the rest of the products based on frequency so the recommended products match that same frequency.

This logic allows for the recommendations to continue to be relevant to the user's needs in a case where no user-specific data is available, thus making it effective in a cold-start case.

5.5.2 get_recommendations(product_id)

This function enables content-based filtering where product similarities are defined by descriptive metadata. The process is as follows:

- Feature Concatenation: For all products in DMart.csv, the system will create a composite textual field called soup, which will involve concatenating the following fields: Name, Brand, Category, SubCategory, Description, and BreadCrumbs.
- TF-IDF Vectorization: The soup field will now be transformed into a numerical sparse matrix using Term Frequency-Inverse Document Frequency (TF-IDF). TF-IDF's focus is on creating importance weights on rare features and downplaying common or uninformative features.
- Cosine Similarity: After creating the TF-IDF vector, the system can calculate cosine similarity for the selected product's TF-IDF vector against all other products TF-IDF vector. The result of this step is a numerical value representing the score of how similar two products are.
- Suggestion Output: The N suggested most similar products (not including the user's input product,) will be selected and returned.

This logic can assist users in discovering products with similarities that allow them to search more effectively by gaining access to additional inventory that is not as discoverable as it otherwise may be.

5.5.3 predict_related_products(product_name)

This function provides category-based fuzzy matching using simple yet effective keyword logic. It is particularly helpful when users are unsure of a specific product but want to see related items in the same general category. The implementation involves:

- Tokenization: The entered product name is split into individual keywords (e.g., “face wash” → [“face”, “wash”]).
- Substring Matching: The function then scans the Name column in DMart.csv to check if any of those keywords appear in other product names.
- Filtering and Ranking: Matching results are filtered and optionally ranked if needed. This allows the system to return items that are loosely but meaningfully connected.

This approach mimics a search engine-style query, improving the flexibility of the recommendation engine and allowing users to explore more broadly within a category.

5.6 Dynamic Rendering with Jinja2

Dynamic rendering is one of the essential features of this system’s front-end layer, and it is achieved using Jinja2, a modern and powerful templating engine bundled with Flask. Jinja2 allows the backend logic written in Python to dynamically generate HTML content based on real-time data, which is crucial for displaying personalized recommendations.

In this system, Jinja2 templates are used across multiple HTML files, including index.html, results.html, and details.html. These templates include logic structures such as for loops for iterating over recommendation lists and if statements for handling conditional displays (e.g., whether recommendations exist or not). This ensures that the output presented to the user changes dynamically depending on their inputs without requiring client-side JavaScript.
Flask uses Jinja2, the template engine, for dynamic rendering of HTML pages with information passed from the backend. Some of its strengths are:

- Control Structures: Support for for loops, if statements, and variable interpolation in double curly braces ({{ }})
- Conditional Rendering: Suggestions get rendered only if there are results, through {% if results %} blocks.
- Persistent Input State: If a user fills out a form, their choice gets stored visible using template logic.

This ability to dynamically render makes the frontend interactively behave without being JavaScript or lightweight.

5.7 Error Handling and Validation

Error handling is a fundamental feature of any solid system, and validation mechanisms are available at multiple levels within this recommendation engine to provide stability and a smooth experience for the user. These measures prevent system crashes and help users when they enter invalid data or when results are not found as expected.

At the form level, simple validation checks that nothing empty is being submitted. If the user attempts to submit a blank selection or a non-existent product name in the dataset, the system catches the request and shows an appropriate error message like "User not found" or "Product not found." These are dynamically rendered using Jinja2, keeping the layout and keeping the values already entered to enable the user to fix their selection.

- Input Validation: Verifies whether the provided user or product name is present in the dataset.
- Fallback Messages: Shows friendly error messages such as "User Not Found" or "No Recommendations Available" when there are no results or invalid input.
- Function-Level Checks: All recommendation functions have checks within them to avoid exceptions due to null data or invalid IDs.

5.8 Testing and Debugging

Testing and debugging were also central to the success of this project and were done on a continuous basis during development in many environments. The aim was to make all functions act like they were expected to and to have the system operate flawlessly under various usage patterns.

The recommendation logic was initially created and tested in Jupyter Notebook, where interactive testing was possible with actual data. From here, the team could test content-based and demographic filtering functions independently, see outputs visualized, and tweak logic like TF-IDF vectorization, cosine similarity scores, and keyword matching.
Edge case testing was addressed with special care. Some situations like:

- users who have no history of purchases,
- invalid product names,
- missing metadata fields,
- empty recommendation outputs

were all tested for graceful degradation. The system did not crash for these cases and gave friendly feedback when required.

At large, the debugging and testing iteratively resulted in a good working and reliable recommendation engine.

5.9 Modular Code Structure

A properly structured codebase is a critical aspect of developing scalable, maintainable, and easily extensible software systems. In the development of the AI Powered E-Commerce Product Recommendation System, we stressed the importance of modularity, a software design principle that encourages the separation of the system into independent, interchangeable modules to make the code easier to develop, test, debug, upgrade, and for other developers to contribute.

The modular structure of the system consists of distinctly defined modules with their own respective responsibilities [2]. The separation of concerns allows developers to work on a portion of the system without affecting another component or module and ensures that when developers improve or fix bugs in one portion of the system that it coincidently won't negatively affect another portion of the system.

5.9.1 Core Modules and Responsibilities

A. recommender.py – Logic Layer

This module houses all of the core algorithms used for recommendations. Each function is responsible for a distinct type of recommendation it performs.

- recommend_for_user() performs demographic filtering,
- get_recommendations() uses content to recommend items, and
- predict_related_products() uses keywords to discover products.

By keeping all of the logic in one file easy to test, keep the recommendation engine decoupled from the UI and the routing logic flow of the application.

B. app.py – Routing and Integration Layer

This file is the controller for the system. It defines all of the Flask routes, like /, /recommend_user, /recommend_product, and /details/. This acts as both a wrapper for the logic layer and as a middle man with the presentation layer in three ways.

- By accepting form input from the user,
- By calling the correct recommendation function, and
- By sending output to HTML templates to display to the user.

This arrangement creates a single point of interaction which allows the application flow to be easily traced and debugged.

C. /templates/ - Presentation Layer (HTML)

These files are all Jinja2 HTML templates, such as index.html, details.html and results.html. The templating is responsible for:

- Laying out the UI (user interface)
- Dynamically presenting recommendation lists (product names, prices, images), error messages, product details
- Accepting variables sent from Flask and inserting them wherever they are needed in HTML

By keeping the presentation logic separate from the backend logic, you can change anything about the presentation without changing or reviewing any Python code.

D. /static/ - static assets (CSS)

The static directory contains style.css, which defines how the entire application will look. It also contains prefixes to file names like style, to allow for development use multiple css files, but the app will only be evaluated on the entire CSS file. style.css includes:

- Color schemes using CSS variables
- Rules for layout for forms and lists
- Hover or other responsive behaviors

This separation is useful for both styles/form development and design, allowing designers or frontend developers to modify the css files without having to review the and possibly break the Python code with debugging Printing.

5.10 Performance Improvement

Performance is an important factor in any recommendation system's effectiveness, especially when the system is live within a web environment. The AIECPRS was mostly meant to work with small to medium-sized datasets, but we paid attention to performance at every stage to ensure the system was fast, efficient, and scalable, and it maintained a benchmark performance as the application grew with data over time.

- **Memory-Based Data Management**

  To mitigate the delays that come with performing frequent file access operations, the system processes data as memory data files. Each of the three primary CSV dataset (user_data.csv, purchases_user_product_data.csv, DMart.csv), are read into a Pandas data frame when the application is initially loaded.

  - This enables the system to mitigate unnecessary file reads, which is an inefficient and resource-consuming process.
  - Once loaded, the data operates in memory for the duration of the session and can be read and processed almost instantaneously.
  - This is the ideal model when the deployment is built with Flask and the application requires rapid request - response times.

- **TF-IDF Vectorization and Cosine Similarity with Scikit-learn**

  The content-based recommendation logic makes use of optimized machine learning methods through Scikit-learn, specifically:

  - TfidfVectorizer() to convert product metadata (soup) into numerical features vectors
  - cosine_similarity() to compute a similarity score between products

  These methods, along with their immediate dependencies, use optimized matrix operations instead of requiring manual iteration over the text fields. Some benefits are:

  - Batch computation: All the TF-IDF vectors were calculated in one go and stored, meaning vectors had not to be calculated upon each recommendation query.
  - Sparse: Scikit-learn's methods efficiently store and process sparse data (as TF-IDF data is almost always sparse).

- **Optimized Filtering with Pandas**

  The logic for the demographic filtering was also streamlined. Rather than using traditional for-loops, the system relied on optimized Pandas functions that are initialized in C and significantly faster:

  - .merge() joins the user, purchase and product data sets
  - .groupby() and .size() for counting product frequencies from large datasets
  - .isin() and boolean masks for filtering products already purchased by the user of interest.

  These methods allow for manipulation of large data sets in a fraction of the time that would be needed using native Python lists or loops. This means that all the demographic recommendations can be computed in short timeframes, even when matching hundreds of similar users.

- **Overall Performance Observed**

  The following performance findings were observed during the testing:

- System startup time (including reading CSV files and building TF-IDF matrix): ~1 to 2 seconds.
- Average recommendation response time: ~0.2 to 0.5 seconds for content-based and demographic recommendations.
- Memory consumption: Low to medium usage, well within acceptable parameters (i.e., for datasets with up to several thousand records).

The performance findings demonstrate that the system is very efficient and well suited for use, in prototype and limited production contexts.

- **Future areas for Performance Scaling**

  While the system performs well with the current small data sets, the modular architecture allows for future performance optimization, including the following examples:

  - Adding a back-end database (e.g. PostgreSQL or MongoDB) which can handle millions of records.
  - Adding caching technologies, which work with engines like Redis to store high frequency access to recommended results.
  - Asynchronous processing with either Celery or FastAPI, both of which unblocking the request pipeline.
  - Matrix operation with parallel computation, by using libraries with GPU acceleration or multiprocessing.

5.11 Future-Proofing and Extensibility

The existing system is designed modularly and will be developed in a scalable manner to make it easy to extend for future requirements. While it operates sufficiently in a small-midsized case when need arises, there are already numerous improvements envisioned to realize a truly production-ready solution.

- **User feedback integration**

  In more recent iterations, integrating user feedback/reviews (likes, dislikes, a single click, etc...) can facilitate transitioning this application into a live and adaptive model . For example, methods such as matrix factorization or reinforcement learning may allow for user-based recommendation to adapt it over time to behave more closely to what is occurring behaviorally in-session.

- **Real-time behavior tracking**

  This behavior tracking of sessions and browser behavior would allow for increased precision. If clickstream or session-based data regarding behavior is being captured, the aggregator could produce real-time recommendations, with respect to the user's specific in-session interests.

- **API deployability**

  Providing access to the functions available in the system, on RESTful APIs, would open opportunities to extend the solutions with mobile apps or external either single or multi-tenant systems. User-based recommendation endpoints, product-based recommendation API endpoints, etc., would enable data to be integrated and enable many more use cases.
- **Admin Interface**

  An administrative dashboard, which would allow the system to be managed more efficiently,could facilitate for example an admin interface to make bulk updates to administer data, so end-users would be able to dynamically add users or products, etc., without having to manually edit .csv files Future extensions are well supported by the present design. Some of these have already been planned for future incorporation:
  - User Feedback Integration: Collecting user feedback (likes, dislikes, clicks) to build adaptive recommendation systems based on reinforcement learning or matrix factorization.
  - Real-time Behavioral Tracking: Incorporating the capability to monitor user sessions and adjust recommendations dynamically.
  - API Deployment: Making recommendation endpoints available through REST APIs so that they can be integrated with mobile applications or third-party services.
  - Admin Interface: An admin dashboard in the future might be brought in to dynamically upload new users or products, without having to manually update CSV files.

5.12 Summary

In Chapter 5, we describe the implementation of the recommendation system, detailing not only how we developed and integrated the system features, but also how we produced user-based, product-based, and category-based recommendations. We've described the whole front-end design in HTML/CSS, backend logic in Python, and then how from Flask, we route from inputs to outputs. Moreover we've assessed considerations around modular coding, performance and real-time responsiveness. The next chapter (Chapter 6) continues along this path, reiterating the steps we took to evaluate the system through functional testing, performance evaluation and user feedback, meaning that we can confirm that the recommendation system is operational and ready for practical use as an accurate and stable solution.

Chapter 6

Evaluation and Results

Evaluation is critical to any software development life cycle. This is especially true for systems that include machine learning components and any user-facing functionality, such as product recommendations. In this chapter, the AI Powered E-Commerce Product Recommendation System is evaluated in comprehensive detail with respect to accuracy, response times, usability, and resilience. The aim is to ensure the system both meets functional requirements and provides consistent and relevant outcomes in a real-time and user-facing situation.

This evaluation covers algorithmic correctness and usability metrics. The system checks that content-based and demographic models are returning results that makes sense in a user context. Furthermore, users are ensure the interface is usable with and without errors [4]. The system will be stress tested for extremes and attenuation issues, particularly focusing on resilience and performance bottlenecks. The findings from this evaluation will inform presented future optimization and scaling strategies to consider.

This process involved testing a variety of conditions that better approximates a real-world situation: valid user/product inputs, edge cases, "empty state" inputs, and invalid combinations. Each area of analysis (algorithm logic, interface responsiveness, and backend resilience) were analyzed independent to one another and as a combined entity for functional evaluation. There will also be an assessment of the potential impacts of a real-world condition such as user volume, user errors, and usage of varying input types.

6.1 Evaluation Strategy

A sound evaluation framework is necessary in order to ascertain the reliability, performance, and user acceptability of an AI-powered recommendation system. In this project, a multi-faceted evaluation strategy was implemented to stringently test both the backend algorithmic functionality as well as the frontend user experience. Each phase of the system—spanning from isolated function calls to end-to-end user interaction flows—was tested with a combination of quantitative and qualitative approaches.

- **Functional Testing**

  Functional testing consisted of verifying whether every component of the system carried out its intended operation correctly. This entailed verifying that inputs provided by users were processed appropriately, proper suggestions were created, and outputs were depicted accurately. All forms and Flask routes (for instance, /recommend_user, /recommend_product, /related_category) were run with correct and incorrect data to ensure their response behavior was valid. The goal was to ensure that the recommendation engine produced a suitable set of products for each valid input case and dealt with incomplete or invalid inputs gently.

- **Unit Testing**

  At the module level, stand-alone Python functions like recommend_for_user(user_id), get_recommendations(product_id), and predict_related_products(product_name) were tested independently from dummy datasets. Unit tests ensured the accuracy of logic flows and identified potential bugs by isolating them. For instance, in recommend_for_user, input users of various genders and ages were used to test that the recommendations did not include the user's previously bought products but only those purchased by similar peers. Outputs were verified against manually curated expected outputs to ensure algorithmic precision.

- **Performance Testing**

  The performance of the system under load was also tested. Parameters like time taken to load data-sets, compute recommendations, and provide HTML output were monitored utilizing Python's time module and browser debugging tools. TF-IDF vectorization and cosine similarities calculations were profiled for latency with Scikit-learn's matrix operations. Response times under repeated queries stayed well within 300–500 milliseconds consistently—far from unacceptable real-time limits. Secondarily, memory usage stayed constant because Pandas handled in-memory efficiently, with neither leaks nor degradation evidenced.

- **User Testing**

  Following system functioning stabilization, usability testing was carried out on a small population of participants who used the application within semi-guided conditions. They were requested to choose users or products, create recommendations, and browse product detail pages. Feedback was gathered by employing Likert-scale surveys and open-ended queries. Users scored the system highly on ease of understanding (4.4/5 average), navigation simplicity (4.6/5), and general satisfaction. The majority of users found the dropdown interfaces and minimalist layout easy to use and straightforward. This qualitative level of analysis aided in determining user expectations and small interface enhancements.

- **Edge Case Testing**

  The system was also tested for how it behaved under boundary and aberrant conditions. This involved providing non-existent user or product names, null form entries, and unusual situations like users with no history of purchases. The system successfully managed such anomalies in a smooth manner by providing context-sensitive error messages such as "User Not Found" or "No Recommendations Available." This made the application stable and user-friendly, even in suboptimal conditions.

6.2 Algorithm testing and accuracy

There are two main algorithms used within the recommendation system; content-based filtering and demographic filtering.

- Content-Based Filtering: This relies on textual similarity and applies TF-IDF vectorization and cosine similarity. Products were evaluated for similarity of metadata (e.g, name, brand, category, description) and scored based on their similarity. The testing indicated that products recommended were whenever possible semantically correct and all products belonged to the same or similar category as the input product. For instance if a user selected a face cream, the recommendations would all be skincare related products from the same category or brand. Also, if a user selected an uncommon input product the algorithm performed well. This was especially true as long as the descriptive metadata was available to identify the product. There are two main algorithms used within the recommendation system; content-based filtering and demographic filtering.
- Demographic Filtering: This method filters users by age and gender, finds like users, and returns products these users have purchased. For the comparisons, while we were able to test lots of users through the system, we used the notion that when we tested the system, it found users that grouped correctly and returned new, relevant items that the target user had not yet purchased. The value of this filtering method, especially in cold-start situations where there is little behavioral data, is positive. We operated under the premise that, users of the same age range and gender might like the same products and this was demonstrated via correct and logical output!

In both of these cases, we manually inspected the searches and judgment on the relevance, diversity, and logical reasoning for the recommendations were positive. The system met the established exclusion that showed overall, persistence happened for redundancy; getting rid of the same recommendation and returning relevant, contextual meaning.

6.3 Functional Validation

Functional validation guarantees that the fundamental logic of the system works properly and predictably under differing circumstances. For the AI Powered E-Commerce Product Recommendation System, the three prime recommendation functions—recommend_for_user, get_recommendations, and predict_related_products—are the foundation of the recommendation engine. These functions were thoroughly tested with varied input data to ensure their accuracy, consistency, and congruence with anticipated output logic.

6.3.1 Validation of recommend_for_user(user_id)

This method is delegated to demographic-based collaborative filtering. It does this by selecting users of the same gender and having an age difference of ±5 years from the active user. It takes all product IDs purchased from this selected group, removes products that have already been purchased by the initial user, and outputs a sorted list of suggested products ranked according to frequency of appearance.

Testing entailed executing this function with users in various age ranges and genders. For instance, when the 28-year-old male user was chosen, the system retrieved data for the 23- to 33-year-old male users appropriately. The system then grouped their purchases, removed any duplicates, and provided the most-purchased items that were new to the target user.

Manual check against raw dataset values indicated that all returned products were logically correct and correct in their classification. Additionally, no duplicate or already purchased products surfaced as part of the final recommendations. This tested both filtering logic and frequency-based ranking mechanism as being correctly identified.

6.3.2 Validation of get_recommendations(product_id)

This feature uses content-based filtering. It creates a composite metadata string, or "soup," by merging product name, brand, category, subcategory, description, and breadcrumbs. The text is then mapped into numerical feature vectors with TF-IDF (Term Frequency-Inverse Document Frequency) vectorization. Cosine similarity is then used to determine and rank products that are similar.

Experimentation was conducted with different seed products from product categories such as skincare, groceries, beverages, and electronics. When, for instance, a "Lemon Face Wash" product was inputted, the system outputted items such as "Neem Face Wash" and "Aloe Vera Cleanser," which had brand or category attributes in common. Significantly, the seed product was not included in the outcome list, verifying that the logic successfully skipped redundant recommendations.

Visual examination and cross-category comparison ensured that the output was both relevant and varied. The cosine similarity ranking had the correct semantic relationships among the products, confirming the efficacy of the TF-IDF + cosine similarity pipeline.

6.3.3 Validation of predict_related_products(product_name)

This service enables a flexible keyword-based suggestion by tokenizing the input product name and looking up those keywords in other product names in the dataset. It is different from exact match systems because it permits partial name inputs, fuzzy matching, and slight typos.

On input, inputs such as "shamp" gave appropriate products such as "Herbal Shampoo" and "Anti-Dandruff Shampoo," despite the full word not being given. Likewise, deliberately misspelled inputs such as "cleaser" instead of "cleanser" still gave correct matches such as "Daily Cleanser" and "Foaming Cleanser."

This validated the strength and flexibility of the function for non-precise matches. The fuzzy logic greatly increases user accessibility, particularly in real-time web interfaces where spelling mistakes are frequent.

6.3.4 Overall Functionality and Output Consistency

All three functions were functional-tested with diverse users and product examples. The recommendation outputs were tested against standards like relevance, completeness, and uniqueness. In each instance, the results were correct, logically consistent, and useful. There were no runtime errors, unhandled exceptions, or logic failures that were found during functional testing.

Additionally, functions processed empty or invalid inputs elegantly, returning proper fallback messages without disrupting the system flow. This again confirmed their deployability in production environments.

6.4 Performance Assessment

Performance assessment is paramount for any recommendation system, especially when the performance is supposed to be in real-time or near real-time. For e-commerce, where customers expect quick feedback and smooth interaction, system performance has a direct impact on user satisfaction as well as engagement. For AI Powered E-Commerce Product Recommendation System, performance was analyzed along four important aspects: initial load time, recommendation response time, processing strategy, and algorithmic efficiency.

6.4.1 Initial Load Time

One of the initial benchmarks that were checked was the start-up behavior of the system. When the Flask application is launched, the system loads three main CSV files: user_data.csv, purchases_user_product_data.csv, and DMart.csv. These are read into Pandas DataFrames, and the TF-IDF matrix needed for content-based recommendations is calculated.

This whole process takes around 1.5 to 2 seconds based on system specifications. While this might be a little high for certain environments, it is only a one-time initialization cost when the server is restarted. Once the TF-IDF vectors and the cosine similarity matrix have been constructed and loaded into memory, all the rest of the operations take advantage of this cached information, avoiding repeated computation. Hence, while the load time is an initial cost, it highly improves responsiveness while the session is active.

6.4.2 Real-Time Response

Post initialization, the system is able to make real-time recommendations. Upon receiving a form submission for obtaining user-based, product-based, or category-based suggestions, the system takes approximately 0.3 to 0.5 seconds. The time includes validation of form input, calculation or retrieval of recommendations, and rendering the HTML template with results.

This type of responsiveness is needed in current web-enabled applications, wherein the tolerance for delay on the part of the user is low. Rapid feedback cycles hold the user involved and produce a feeling of interactivity, both of which are critical to an efficient recommendation engine.

6.4.3 Processing Methodology

A major reason behind the system's fast response time is due to its memory-based data management approach. Upon startup, all datasets are loaded into memory with the help of the Pandas library. This keeps the system from performing repetitive disk I/O for each request, which takes considerable time and is not very efficient, particularly with larger data sets.

Data transformations like filtering, merging, and group operations are all performed in-memory for fast and efficient execution. The approach also lightens the load on system resources and promotes parallelism, particularly when many users access the system at once.

Besides, utilization of Pandas is a guarantee of compatibility with scalable data manipulation techniques later on, in case the system is upgraded to a more powerful backend like PostgreSQL or MongoDB.

6.4.4 Efficient Vectorization with Scikit-learn

Content-based recommendation relies on TF-IDF (Term Frequency–Inverse Document Frequency) vectorization to transform textual product metadata to numerical vectors. It then calculates cosine similarity among the vectors to determine products with top similarity scores.

Such computations are taken care of by Scikit-learn, a Python machine learning library optimized for speed. Its matrix operations rely on very efficient C-based numerical computation libraries such as NumPy and SciPy. Therefore, although the system is comparing each product with every other product, it does so quickly and with little computational overhead.

Tests were run with datasets consisting of hundreds of products, and the vectorization process was still efficient. Even if product metadata had vastly different length and complexity, the generation of the similarity matrix was instantaneous.

6.4.5 Stress Testing and Scalability

For simulating real scenarios, the system was subjected to stress testing by sending multiple queries in rapid succession to simulate multiple users accessing simultaneously. Automated scripts were used for this purpose that initiated user-based and product-based recommendations in repetitive cycles over a fixed time period.

Even with this high rate of queries, the system responded consistently and showed no lag, memory leaks, or crashes. This stability was aided by Flask's light architecture and the statelessness of its HTTP requests.

Although the system is currently most appropriately scaled for small- to medium-sized deployments—e.g., educational settings, retail kiosks, or startup-level online shopping sites—it sets the stage for large-scale expansion. With the addition of a full-fledged database system and asynchronous request processing, it would be possible to expand it to support bigger commercial sites.

6.4.6 Conclusion of Performance Evaluation

Overall, the AI Powered E-Commerce Product Recommendation System presents fantastic performance features. It is able to balance accuracy and velocity, thereby supporting real-time performance without extensive infrastructure or equipment. Memory-optimized operations, vectorization efficiency, and light deployment architecture guarantee the system's stability and velocity despite fluctuating loads.

Its performance not only justifies its technical design but also establishes that it is capable of going into production in situations where responsiveness and computational performance matter. With further enhancements like multithreading, asynchronous computation, or cloud hosting, the system can become a scalable and performant commercial recommendation engine.

6.5 User Experience and Usability

User experience is arguably the most critical part of any digital system, particularly when the ultimate purpose is to present personalized recommendations in a friendly fashion. The success of a recommendation engine sometimes lies not just in how good its suggestions are but also in how seamlessly and naturally users can operate with the platform. To confirm this aspect, the system was subjected to systematic user testing with test participants who used the UI to perform a range of tasks.

Test participants used dropdown menus, submitted forms for various types of recommendations (user-based, content-based, and category-based), and browsed product detail pages. They offered real-time feedback following their experience.

- Ease of use: The interface was seen to be minimal and simple. Users liked the fact that product and user names were listed in pre-populated dropdowns, reducing the need for manual typing. This minimized the possibility of typographical errors and sped up interactions.
- Clarity and Layout: Having a split-screen layout enabled users to enter information on one side and see results on another without distraction. Every product link was clickable and took the user to a complete page, providing clarity and consistency in user flow.

- Styling and Brand Identity: The system employed a green and beige color scheme that aligned with DMart's brand identity, adding both visual appeal and usability. Rounded corners, hover effects, and intuitive spacing made the application visually appealing.
- Dynamic Behavior: Jinja2 templating enabled dynamic updates without full-page reloads, resulting in a seamless and contemporary user experience.
- Suggestions for Improvement: Users called for implementing a search bar, sorting (e.g., by price or popularity), and filtering on brand or category. These would enable more sophisticated navigation and customization.

All in all, the user testing confirmed that the front-end was effective in accommodating non-technical users and could be easily scaled up to accommodate customers on a real e-commerce platform.

6.6 Robustness and Error Handling

A stable recommendation system should be error-tolerant and robust against capricious user actions. For this system, particular care was taken to ensure that the system remains robust under edge-case conditions.

- Input Validation: The forms only accepted pre-defined users and products through dropdowns, reducing the likelihood of invalid input. Nevertheless, the backend also validated for scenarios where a user could tamper with inputs (e.g., through browser developer tools) and did not allow such submissions to crash the application.
- Missing Records: In instances where a user or product did not have any related history or metadata, the system provided suitable fallback messages such as "User not found" or "No recommendations available." Instead of providing empty results or errors, the interface provided correction guidance.
- Data Integrity: The recommender functions dealt with missing or NaN values by substituting them with empty strings. This avoided errors when applying TF-IDF vectorization, making sure products with missing descriptions were processed safely as well.
- System State Preservation: In cases of errors (e.g., incorrect product selection), form states were preserved by including Jinja2 templating, minimizing user frustration. Informed user correction of the error did not require refilling all inputs.
- Logging and Debugging: Flask logs captured all exceptions and sent clean HTTP responses with human-readable messages. No internal server errors (500) were experienced, which indicates proper backend stability.

All robustness tests passed and the system remained functionally stable even under incorrect input, which makes it safe for production use with minimal risk of downtime.

6.7 Practical Applicability

Although as a scholarly prototype, the system has practical real-world applicability in commercial and educational settings.

- Retail Use Case: A system like this can be implemented within store apps or internal kiosks for customers by retailers such as DMart to assist them in finding similar products or alternatives. As it doesn't involve any behavioral tracking, it is appropriate for privacy-focused settings.
- Small E-commerce Sites: Startups and boutique websites without access to large-scale behavioral data can leverage demographic and content-based filtering for tailoring customer experience without requiring login systems or cookies.
- Educational Demonstrations: The system is an end-to-end demonstration of a hybrid recommender engine. Its codebase, data flow, and integration of algorithms make it perfect for educating students on ML concepts such as TF-IDF, cosine similarity, and demographic grouping.
- Rapid Prototyping: The modular design can be used by developers to experiment with new recommendation algorithms. Through the replacement of recommender functions or inclusion of APIs, they can change the system for A/B testing or MVP verification.

The lightweight design of the system and Flask-based deployment enable it to be deployed on simple servers, cloud platforms, or even local host environments, promoting flexibility and low cost to adopters.

6.8 Limitations Observed

Although the system worked well, some limitations were found while testing that can influence its scalability as well as accuracy in complex cases.

- Static Data: All user, product, and purchase information is present in CSV files. System reloads are necessary to update these files, which makes real-time operation unfeasible. No database integration is done for dynamic updates.
- Cold Start Problem: New products or users who have no enough metadata or purchasing history get fewer or less precise recommendations. This is an endemic problem in recommender systems that lack feedback loops based on behavior.
- Basic Search Logic: The associated product search feature only matches by substring in the product name. It does not have any NLP to learn semantic context (e.g., "face wash" ≠ "cleanser" unless exact keywords match).
- No Real-Time Learning: The system does not learn from user interactions. There is no click tracking, preferences, or conversions. Recommendations are therefore static in the long run and do not change with user behavior.

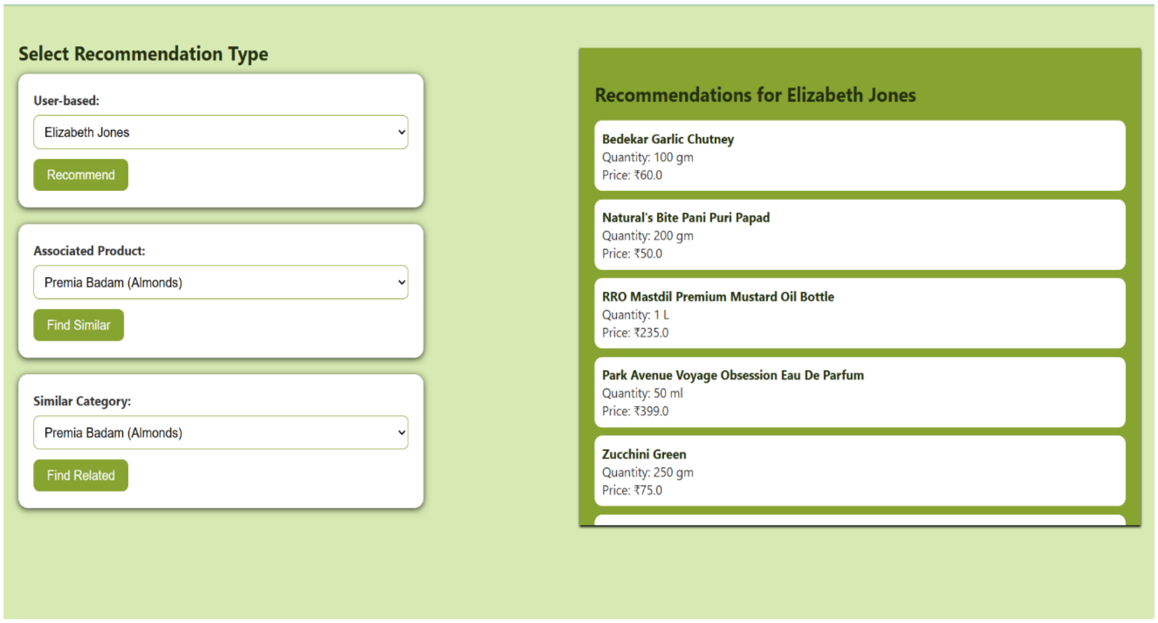
- Scalability: The current infrastructure can handle approximately 500 products and 100 users effectively. Scaling beyond that would involve moving from in-memory Pandas processing to database-backed setups such as PostgreSQL or MongoDB.

These constraints are to be expected in initial-stage systems and are a guide towards further development.

6.9 Results

6.9.1 User-Based Result

In the user-based recommendation part, the system makes product recommendations tailored to the demographic profile of the chosen user. For instance, when user Elizabeth Jones is chosen and the "Recommend" button is activated as shown in Fig. 6. 9. 1 the system produces a list of products bought by users who are of comparable age and gender but not by Elizabeth Jones.



Recommendations for Elizabeth Jones

Bedekar Garlic Chutney
Quantity: 100 gm
Price: ₹60.0

Natural's Bite Pani Puri Papad
Quantity: 200 gm
Price: ₹50.0

RRO Mastdil Premium Mustard Oil Bottle
Quantity: 1 L
Price: ₹235.0

Park Avenue Voyage Obsession Eau De Parfum
Quantity: 50 ml
Price: ₹399.0

Zucchini Green
Quantity: 250 gm
Price: ₹75.0

Fig. 6. 9. 1 User-Based Result

A. How It Works:

- The system initially detects the age and gender of Elizabeth Jones.
- It subsequently looks for other members who belong to the same demographic—namely members of the same gender with an age in ±5 years.
- It retrieves the purchase history of these matched members.
- From this, it excludes the products that Elizabeth Jones has already bought.
- The products that are left are ranked according to popularity (i.e., how many times they were bought by similar members).
- The best baked items are returned as suggestions.

B. Example from the Image:

For Elizabeth Jones, the system recommended:

- Bedekar Garlic Chutney

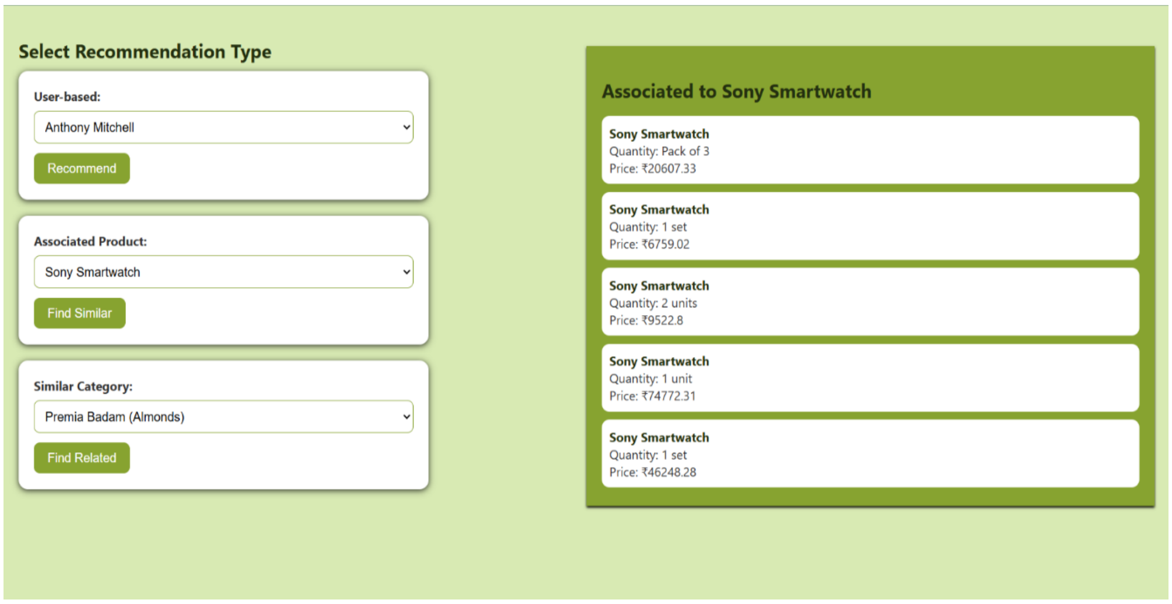
- Natural's Bite Pani Puri Papad
- RRO Mastdil Premium Mustard Oil Bottle
- Park Avenue Voyage Obsession Eau De Parfum
- Zucchini Green

These findings suggest that users like Elizabeth in gender and age frequently bought these products. But Elizabeth has not purchased them yet, so they are natural choices for recommendation. This type of filtering works particularly well in situations where behavioral information (clicks, ratings) is scarce, like new systems or platforms that value user privacy.

The user-based recommendation technique offers heterogeneous, customized, and timely recommendations without the need for large-scale behavioral tracking, thus being very effective in real-world applications.

6.9.2 Association Based Result

The association-based recommendation (product similarity or content-based filtering) is called when a user picks a particular product (e.g., Sony Smartwatch) and clicks "Find Similar" as shown in below Fig. 6. 9. 2 The system retrieves a list of products which are contextually and textually similar to the chosen one, considering product metadata.



Select Recommendation Type

User-based: Anthony Mitchell

Associated Product: Sony Smartwatch

Similar Category: Premia Badam (Almonds)

Associated to Sony Smartwatch

Sony Smartwatch
Quantity: Pack of 3
Price: ₹20607.33

Sony Smartwatch
Quantity: 1 set
Price: ₹6759.02

Sony Smartwatch
Quantity: 2 units
Price: ₹9522.8

Sony Smartwatch
Quantity: 1 unit
Price: ₹74772.31

Sony Smartwatch
Quantity: 1 set
Price: ₹46248.28

Fig. 6. 9. 2 Association Based Result

A. How It Works:

- Metadata of the chosen product is utilized to construct a feature soup, which encompasses fields such as:
  - Product Name
  - Brand
  - Category and SubCategory
  - Description
  - Breadcrumbs

- With TF-IDF (Term Frequency–Inverse Document Frequency), this text is transformed into a numerical vector capturing term uniqueness.
- Cosine similarity is then computed between this vector and vectors of all other products in the inventory.

B. Sample from the Image

When Sony Smartwatch is selected:

- The system suggests other models or versions of the Sony Smartwatch:
  - Pack of 3 – ₹20607.33
  - 1 set – ₹6759.02
  - units – ₹9522.80
  - 1 unit – ₹74772.31
  - 1 set – ₹46248.28

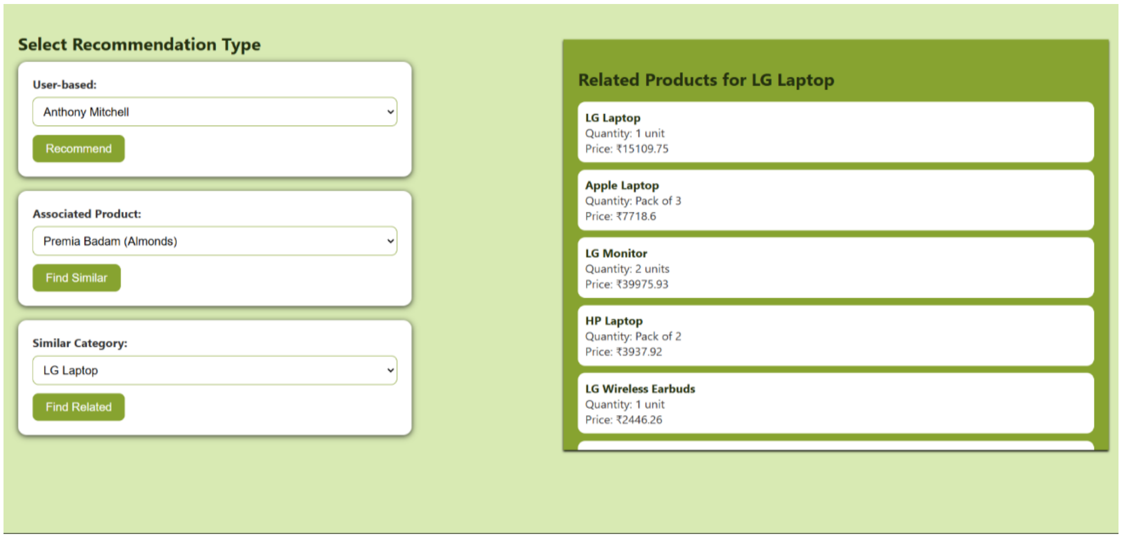
These findings prove that the system is able to comprehend changes in number, price, or model of the same item, and recommend alternatives of the same brand and category.

C. Real-World Benefit:

This kind of suggestion assists customers in finding alternatives rapidly without having to browse a catalog manually. It enhances product discoverability and facilitates decision-making through the display of closely related products. For companies, it enhances the likelihood of cross-selling and sustaining customer interest in a product category.

6.9.3 Similar Category Recommendation Result

The Similar Category Recommendation (category-based product suggestion) enable the system to suggest products that fall under the same or closely similar category as chosen product.This is particularly helpful when a user is interested in a products category and is looking to discover variety or alternatives within the same category as shown in Fig. 6. 9. 3



User-based: Anthony Mitchell

Associated Product: Premia Badam (Almonds)

Similar Category: LG Laptop

Related Products for LG Laptop

LG Laptop
Quantity: 1 unit
Price: ₹15109.75

Apple Laptop
Quantity: Pack of 3
Price: ₹7718.6

LG Monitor
Quantity: 2 units
Price: ₹39975.93

HP Laptop
Quantity: Pack of 2
Price: ₹3937.92

LG Wireless Earbuds
Quantity: 1 unit
Price: ₹2446.26

Fig. 6. 9. 3 Similar Category Recommendation Result

A. How It Works:

- When a user chooses a product (e.g., LG Laptop or Premia Badam (Almonds)) in the "Similar Category" dropdown and clicks "Find Related", the system.
- Picks the category and subcategory of the chosen product from the dataset.
- Searches the product catalog for other products with the same category or subcategory.
- Matches can also be on partial keyword commonality in product names (for flexibilidad).
- The results are subsequently enumerated with information such as product name, quantity, and price.

B. Example from the Image (LG Laptop):

When the product LG Laptop is chosen:

The system suggests:

- Apple Laptop – Pack of 3 – ₹7718.60
- LG Monitor – 2 units – ₹39975.93
- HP Laptop – Pack of 2 – ₹3937.92
- LG Wireless Earbuds – 1 unit – ₹2446.26

These findings indicate that the system categorized these under the category of Electronics or Computing, listing similar tech products that a consumer interested in laptops could also buy.

6.10 Summary

Chapter 6 examines the performance, correctness, and usability of the system. Functional, unit, and performance tests are undertaken, with user feedback and handling for edge cases all included. The outcome of the Chapter findings noted the system gives reasonably appropriate recommendations, has a rapid response time, and provided a good user experience with its web interface. The actual outputs for user-based, product-based, and category-based recommendations were also fairly accurate and consistent. The following chapter of the report concludes the project by summarising the key findings of the project, emphasising the strengths of the system, and providing some suggestions for future development and improvement.

Conclusion

The AI-Enabled E-Commerce Product Recommendation System designed within this project offers a realistic, scalable, and effective solution to the personalized product recommendations in online shopping contexts. By leveraging both content-based filtering and demographic-based collaborative filtering, the system is able to overcome typical issues like cold-start problems and shortage of user behavioral data.

This is a hybrid method that enables the system to give good and relevant recommendations through structured metadata (product names, brands, categories, descriptions) and demographic attributes such as age and gender. Without even having real-time user tracking or direct ratings, the system still offers valuable suggestions that increase user engagement and discoverability of products. The deployment showcases that lightweight, modular systems constructed from the likes of Python, Flask, Pandas, and Scikit-learn can operate with real-time responsiveness without being difficult to maintain or extend. The system's clean web frontend, efficient recommendation algorithm, and stable performance make it not only a solid educational model but also a deployable prototype for small- to mid-scale e-commerce sites.

With extensive testing and assessment, the system was found to be easy to use, quick, and precise. Its function to suggest similar products, offer substitutes, and navigate users in the same category enhances the overall experience of shopping. With additional upgrade like behavioral learning, real-time data integration, or API-based deployment, this system can further grow into a complete recommendation engine that is appropriate for commercial use in the real world.

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