

T.R.
GEBZE TECHNICAL UNIVERSITY
GRADUATE SCHOOL

IMPROVEMENT OF E-COMMERCE RECOMMENDER SYSTEMS
WITH ARTIFICIAL INTELLIGENCE CHAT ROBOTS

EMİR ŞAHİN

A THESIS OF MASTER OF SCIENCE INDUSTRIAL
ENGINEERING

ADVISOR: ASSIST. PROF. DR. AYŞE CİLACI TOMBUŞ

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LİSANSÜSTÜ EĞİTİM ENSTİTÜSÜ

YAPAY ZEKA SOHBET ROBOTLARI İLE E-TİCARET
ÖNERİ SİSTEMLERİNİN İYİLEŞTİRİLMESİ

EMİR ŞAHİN

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ABSTRACT

Nowadays, online shopping and e-commerce are becoming increasingly important. Customers can easily access products and shop through various shopping platforms. However, this convenience also creates problems such as overload of information and difficulties in accessing natural products. In this case, artificial intelligence-based recommendation systems aim to improve consumers' shopping experiences. This thesis examines how artificial intelligence-based recommendation systems can make online shopping experiences more effective.

In particular, the effectiveness of an algorithm developed to recommend products that may match customers' needs by analyzing their past purchasing experiences and movements on the site is observed. In this context, it is considered how recommendation systems can be developed by using natural language processing models such as ChatGPT. These systems are designed to provide personalized product recommendations by evaluating consumers' previous purchases, site movements and other relevant data. In the study, the performances of versions of ChatGPT (e.g., ChatGPT 3.5, ChatGPT 4, ChatGPT 4.5 Turbo, ChatGPT-4o) were compared to determine which model could provide better recommendations.

In the first part of the study, the data set to be used was collected and the necessary preliminary examination steps were carried out on the collected data set. In the next step, personalized recommendation systems were developed and tested using ChatGPT models. Various parameters have been used to evaluate the performance of personalized recommendation systems. These criteria include realism, consumer satisfaction, and speed of system performance.

As a result of this thesis, a study was developed that aims to determine the preferences and needs of customers and recommend the most appropriate products. Real-time user experiences and comments were also taken into account to measure the performance and results of our recommendation system.

As a result of the study, this thesis stands out as an important step in understanding how artificial intelligence-based personalized recommendation systems can improve internet e-commerce shopping usage. Focusing especially on consumer needs, the thesis form the basis for further research in this field. Unlocking the power of artificial intelligence and language models in online shopping is important in terms of both improving the customer experience and generating commercial benefits.

Keywords: Chat Robots, Recommender Systems, Artificial Intelligence, Machine Learning, ChatGPT, E-Commerce, Personalized Recommendation, Algorithm

ÖZET

Günümüzde, çevrimiçi alışveriş ve e-ticaret giderek daha da önemli hale gelmektedir. Müşteriler, farklı alışveriş platformları aracılığıyla ürünlere kolayca erişebilir ve alışveriş yapabilirler. Ancak bu kolaylık, bilgi fazlalığı ve doğal ürünlere erişimde zorluklar gibi sorunları da beraberinde getirmektedir. Bu noktada, yapay zeka tabanlı öneri sistemleri tüketicilerin alışveriş deneyimlerini geliştirmeyi hedeflemektedir. Bu tez, yapay zeka tabanlı öneri sistemlerinin çevrimiçi alışveriş deneyimlerini nasıl daha etkili hale getirebileceğini incelemektedir.

Özellikle, müşterilerin geçmiş satın alma deneyimlerini ve site üzerindeki hareketlerini analiz ederek onların ihtiyaçlarına uygun ürünleri öneren bir algoritmanın etkinliği gözlemlenmiştir. Bu bağlamda, ChatGPT gibi doğal dil işleme modelleri kullanılarak öneri sistemlerinin nasıl geliştirilebileceği ele alınmıştır. Bu sistemler, tüketicilerin önceki satın alımlarını, site hareketlerini ve diğer ilgili verileri değerlendirerek kişiselleştirilmiş ürün önerileri sunmak için tasarlanmıştır. Çalışmada, ChatGPT'nin çeşitli sürümleri (örneğin, ChatGPT 3.5, ChatGPT 4, ChatGPT 4.5 Turbo, ChatGPT-4o) karşılaştırılarak hangi modelin daha iyi öneriler sunabileceği belirlenmiştir.

Çalışmanın ilk bölümünde kullanılacak veri seti toplanmış ve toplanan veri seti üzerinde gerekli ön inceleme adımları gerçekleştirilmiştir. Bir sonraki aşamada, ChatGPT modelleri kullanılarak kişiselleştirilmiş öneri sistemleri geliştirilmiş ve test edilmiştir. Kişiselleştirilmiş öneri sistemlerinin performansını değerlendirmek için çeşitli parametreler kullanılmıştır. Bu kriterler arasında gerçeklik, tüketici memnuniyeti ve sistem performansının hızı yer almaktadır.

Bu tezin sonucunda, müşterilerin tercihlerini ve ihtiyaçlarını belirlemeyi ve en uygun ürünleri önermeyi amaçlayan bir çalışma geliştirilmiştir. Öneri sistemimizin performansını ve sonuçlarını ölçmek için gerçek zamanlı kullanıcı deneyimleri ve yorumlar da dikkate alınmıştır.

Çalışmanın sonucunda bu tez, yapay zeka tabanlı kişiselleştirilmiş öneri sistemlerinin internet e-ticaret alışveriş kullanımını nasıl geliştirebileceğini anlamada önemli bir adım olarak öne çıkmaktadır. Özellikle tüketici ihtiyaçlarına odaklanarak, tez bu alandaki gelecekteki araştırmalar için bir temel oluşturmaktadır. Yapay zeka ve dil modellerinin çevrimiçi alışverişteki gücünün açığa çıkarılması, müşteri deneyimini iyileştirme ve ticari faydalar sağlama açısından önemlidir.

Anahtar Kelimeler: Sohbet Robotları, Öneri Sistemleri, Yapay Zeka, Makine Öğrenimi, ChatGPT, E-Ticaret, Kişiselleştirilmiş Öneri, Algoritma

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LIST OF SYMBOLS AND ABBREVIATIONS

NLP	: Neuro Linguistic Programming
MySQL	: My Structured Query Language
URL	: Uniform Resource Locator
XML	: Extensible Markup Language
JSON	: JavaScript Object Notation
GPT	: Generative Pre-trained Transformer
AI	: Artificial Intelligence
ID	: Identification Number
RPM	: Requests Per Minute
RPD	: Requests Per Day
TPM	: Tokens Per Minute

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1. INTRODUCTION

Online shopping, as one of the significant innovations of the digital age, enables consumers to access products and services quickly and easily. Although the wide range of products and the ease of access provided by the internet have increased the popularity of online shopping, users often face information overload and difficulties in finding the right product. At this point, artificial intelligence-based recommendation systems aim to improve users' online shopping experiences.

Personalized e-commerce recommender systems are algorithms that analyze users' past experiences, movements and preferences in order to provide personalized recommendations. These systems aim to provide a better shopping experience to consumers on online shopping sites, as well as to increase user satisfaction and increase purchasing volume to a high level. This study examines the structure of artificial intelligence-based recommendation systems to improve consumers' online shopping experiences. It aims to evaluate the general functioning and results of an e-commerce algorithm developed to offer products that comply with the requirements, especially by evaluating consumers' previous shopping experiences and their behavior on the sites.

For these purposes, chatbot robots like ChatGPT etc. are used in the study and how advanced natural language models can be used in personalized recommendation systems is evaluated. ChatGPT stands out as a groundbreaking model in the field of natural language processing (NLP) with its ability to evaluate text data and extract human-like responses. In this thesis, it compares the performances of different models of ChatGPT (for example, ChatGPT 3.5, ChatGPT 4, ChatGPT 4.5, ChatGPT 4o) in order to determine which models can produce more effective recommendations. Various parameters were used to determine which of the models could produce more effective recommendations. In addition, the structures used for ChatGPT algorithms are designed to provide different suggestions for the user's subsequent purchase, including product recommendations, product categories, purchase dates and budget.

In the first part of the thesis, a data set containing consumer past shopping values was collected and the necessary first steps were taken with this data set. The consumer data set includes users' previous shopping data and movements within e-commerce applications. For example, products from a specific store were included in the dataset and combined with users' previous purchase data. The data is constructed to provide personalized recommendations based on the user's purchasing history.

The methods used in the thesis include evaluating users' purchase histories and product details in order to provide personalized recommendations using OpenAI's (Artificial intelligence research platform) language techniques and embedded representation techniques. A study was developed to recommend the most suitable products by evaluating users' previous shopping data sets. This system is highly effective in recommending similar products by evaluating users' previous purchasing behavior.

In particular, ChatGPT models were used to calculate the similarities between products and to recommend suitable products based on users' past purchases. The process was carried out to understand the needs of consumers and provide a truly personalized shopping experience. Different parameters such as realism, customer satisfaction and performance have been used to measure the success of recommendation systems.

Without focusing on a specific product category, many products have been evaluated to determine the needs of users. User needs analysis was carried out taking into account factors such as previous purchase data. During the analysis, a model was developed to determine the most suitable products by determining the needs of the users.

The success of personalized recommendation systems was evaluated by taking into account real-time user experiences and feedback. Uncovering the power of artificial intelligence and natural language processing models in e-commerce online shopping is important in terms of both increasing user satisfaction and providing commercial benefits.

This study aims to contribute to explaining how personalized recommendation systems using artificial intelligence can improve online user shopping transactions.

2.

2. LITERATURE REVIEW

Our thesis focuses on developing a personalized product recommendation system using artificial intelligence (AI) techniques to further enhance the online shopping experience. The main goal of our thesis involves complex analysis of users' past data (past purchases, add-to-cart actions, etc.) and generates personalized product recommendations. This approach aims to reduce significant problems associated with online shopping, such as information overload and difficulty in finding suitable products, by providing an intuitive recommendation experience. Our main goal is to use extensive past user data to improve and personalize recommendations. This methodology is designed to offer a high level of customization by analyzing past user behavior and preferences. In this respect, our thesis is in line with the findings of Duwadi (2023), who investigated the effectiveness of using past data in retail recommendation systems. Duwadi's work emphasizes the value of past data in increasing recommendation accuracy and user satisfaction, which supports the focus on using past interactions to increase the relevance of product recommendations. Our thesis innovates with the trend towards automation by eliminating the need for users to provide input to the system (sending messages, choosing from ready-made questions, etc.) to receive recommendations. In our thesis, the robot proactively generates recommendations based on the data collected and the observed user behavior as a result of its operation. This design choice is supported by Zhang et al. (2024) in their study titled **“Guiding User Experience of ChatGPT-based Conversational Recommendation Systems: Effects of Quick Guidance and Recommendation Space”**. This study is similar to our goal of minimizing user input requirements to facilitate the recommendation process. The technological basis of our recommendation system includes various iterations of the ChatGPT model, such as ChatGPT 3.5-Turbo, 4, 4-Turbo, 4o. These models are evaluated together with their ability to provide effective and personalized recommendations in various e-commerce scenarios. This approach is similar to the comprehensive review conducted by Al-Hasan and Sayed (2024) in their study titled **“From Traditional Recommendation Systems to GPT-Based Chatbots: A Survey of Recent Developments and Future Directions”**. Their work addresses the advances in GPT technologies and their impact on personalization, supporting us to use these advanced models to increase recommendation precision.

The thesis additionally extends the application of chatbot-driven recommendation systems beyond specific industries such as fashion to a broader e-commerce context. This extension is inspired by Wanick's (2022) work titled **“Chatbot Design Approaches for Fashion E-commerce: An Interdisciplinary Review”**. This work examines how chatbots can be effectively used in fashion e-commerce and provides insights into their applications across various product categories. This supports the broader application of chatbot technology to improve user interactions across different e-commerce environments.

The final part of our thesis includes a rigorous evaluation of the performance of ChatGPT in providing personalized recommendations across various e-commerce scenarios. This evaluation is based on Palma et al.'s (2023) work titled **“Evaluating ChatGPT as a Recommendation System: A Rigorous Approach”**. In this study, a detailed analysis of the effectiveness of ChatGPT as a recommendation system is presented, which provides a fundamental foundation for exploring its capabilities in various online shopping contexts. This alignment highlights the importance of our thesis in advancing the application of ChatGPT in recommendation systems. To summarize, our thesis integrates the insights from these studies to advance the field of AI-powered personalized recommendation systems. In particular, by utilizing the latest developments in AI and recommendation models through the use of ChatGPT models, we aim to increase the quality and similarity of product recommendations, and thereby improve customer satisfaction and operational efficiency in online shopping platforms.

3. PRODUCT RECOMMENDATION STEPS

The aim of the thesis is to evaluate the use of artificial intelligence-based personalized recommendation systems to improve the performance of online shopping applications. It aims to evaluate the performance of a structure established in order to recommend products suitable for their needs, especially by evaluating consumers' past purchasing experiences and their behavior within the sites. For this purpose, the following specific target criteria have been determined:

Understanding User Behavior: It includes the analysis of consumers' behavior and preferences during online shopping in order to understand individual purchasing behavior. The analysis includes information obtained from data sources such as users' previous purchase data, their movements in the application, and comments for the products.

Development of Personalized Recommendation Systems: This includes designing personalized recommendation systems to improve users' purchasing experiences. Recommendation systems aim to determine suitable products for users by evaluating past data and current models. Advanced natural language models such as ChatGPT have been used in the development of personalized recommendation systems.

Comparison of the Performance of Different Models: By comparing the performance of recommendation systems, it aims to determine which of the ChatGPT models can provide more effective recommendations. Parameters such as accuracy, user satisfaction and system speed are used in the comparisons.

Preliminary Processing of Data and Application of Analysis Methods: It involves finding a large data set containing user data and performing important analysis steps within the data set. It involves organizing and making the data ready for analysis. Operations such as removing products belonging to a specific store from the data and including them in the users' previous purchase data are carried out.

Evaluation of the Performance of Recommendation Systems: This is the stage of evaluating the performance and user satisfaction of the developed recommendation

systems. At this stage, real-time consumer experiences and comments are evaluated to analyze whether the recommendation systems meet the needs of the users.

Analyzing Large Product Models: It involves analyzing large product lists without focusing on a specific product list in order to determine users' different product preferences. The desired goal is to develop a system that will recommend the most suitable products to users based on analysis.

Sharing Results and Evaluations: This stage involves evaluating all the results obtained and providing predictions showing that artificial intelligence-based recommendation systems can be used more effectively in online shopping. The study aims to make significant contributions to explaining how artificial intelligence and existing language models can be made more efficient and user-centered in online shopping applications.

It is thought that all the results obtained throughout the study can contribute to both academic and practical applications. Personalizing and improving online shopping experiences is of great importance in terms of increasing user satisfaction and supporting commercial success. In this sense, evaluating the potential of artificial intelligence recommendation systems will form an important basis for future research.

4. DATA ANALYSIS

This data set contains purchase transaction details made by different users on a particular e-commerce application. The following fields were collected to understand user past behavior and preferences:

User Shopping History Dataset

This dataset contains details of purchases made by various users from a specific e-commerce platform. The following fields have been collected to understand user behaviors and preferences:

- **User's ID (user_id):** A unique identifier for the each user.
- **Purchasing Time (purchase_time):** The date and time the purchase was made. This informations are used to analyze changes in users' shopping habits over time.
- **Device (device):** The type of device used for the purchase (e.g., mobile, desktop). This data helps determine which devices are preferred by users.
- **Country (country):** The country where the user made the purchase. This information is used to examine shopping behaviors by geographical region.
- **URL (url):** The URL link of the product lists where the purchase was made.
- **Price (price):** The total cost of the purchase.
- **Products (products):** Detailed information about the products purchased during the shopping session. This field is stored as a JSON list and includes information such as the ID, category, and price of each product.

An example of shopping data is as follows:

Parameter	Value
User ID	12345
Purchase Time	2024-05-01T13:45:30
Device	Mobile
Country	Turkey
URL	example.com/product123
Total Price	29.99
Product ID	987
Category	Erkek&Aksesuar
Item Price	19.99

Table 1: Example of User Shopping History Data Set

Records of user product purchases and add-to-cart actions between October 1, 2023, and May 10, 2024, are available. The user history data file contains 9,338 rows of records. There can be multiple purchase records for the same user, as well as customers with only one past purchase record. Each user has 11 parameters (userhash, timeepoch, timereadable, device, browser, os, language, url, currency, totalprice, products).

The user data file contains unique "userhash" values, indicating that information from 3,049 different users was used in the analysis.

Product Inventory Dataset

This dataset includes details of all products available on the e-commerce platform. It provides information about the current stock status and characteristics of the products. The dataset includes the following fields:

Product ID (product_id): A unique identifier for each product.

Price (price): The sales price of the product.

Category (category): The category to which the product belongs. For example, "Men > Accessories," "Unisex > Accessories > Beanie," "Men > Textile > Fleece Tops."

Stock Status (availability): The stock status of the product (e.g., "In Stock," "Out of Stock").

An example of product data is as follows:

Parameter	Value
Product_ID	987
Availability	In Stock
Sales_Price	19.99
Product_Category	Erkek&Aksesuar

Table 2: Example of Product Inventory Data Set

Within the product inventory file, there are 1268 rows of ID records. This information indicates the presence of 1268 different product details used in analyses. Additionally, all products are maintained in the same format template.

Each product has 22 parameters: ID, Model Number, Discount Percentage, Link, Brand, GTIN, Title, Description, Price, Sale Price, Condition, Availability, Product Category, Google Product Category, Image Link, Additional Image Link, Custom Label 0, Custom Label 1, Custom Label 2, SBO, Product Material, and Analytics SKU.

The Product Inventory Data Set Example analyzes these 22 parameters.

4.1. Data Processing and Analysis

The User Shopping History Data Set is in Excel file format and is read and processed using the pandas library. The product inventory data set is in XML format and is read and processed using the xml.etree.ElementTree library. During these processes, relevant information is extracted from both data sets.

Since the user shopping history data set stores products in JSON format, the JSON library is used to process and analyze this data. On the other hand, the product inventory data set is in XML format, hence the xml.etree.ElementTree library is employed to process and analyze this data. Furthermore, during the processing and analysis of the data sets, text embedding (textual representation embedding) is used to

calculate similarities between products. For this task, a language model named "text-embedding-ada-002" is utilized.

text-embedding-ada-002 is a language model developed by OpenAI. This model replaces previous models in tasks such as text search, text similarity, and code search, surpassing the functional capabilities of the previous most capable model, Davinci, and reducing its cost by 99.8%. Embeddings are numeric representations of concepts, facilitating computers' understanding of relationships between these concepts. The text embedding method applies these embeddings to text data, allowing for the determination and analysis of similarities between texts, thereby expressing semantic similarities numerically and making them analyzable.

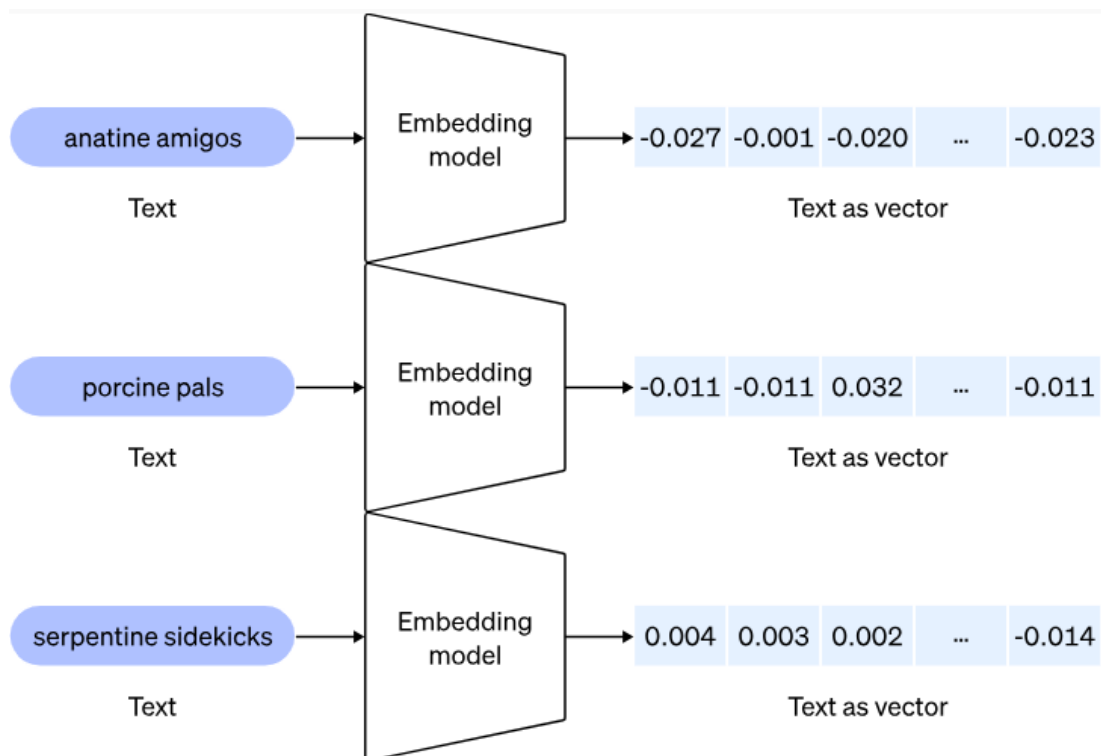


Figure 1: Embedded Models and Vector Forms

4.2. Processing Procedure

4.2.1. Reading User Shopping History:

The userhash (user ID) value is obtained from the user, and using this value, the relevant user's shopping history is read from the Excel file. The IDs and other details (category, price, etc.) of the products purchased by the user are added to a Python set.

4.2.2. Reading Product Inventory:

The product inventory file in XML format is read, and using the product IDs, products that match those purchased by the user in the past are identified. Stock status, price, and category information for each product are retrieved and stored in a Python list.

4.2.3. Recommendation System:

The user's historical shopping data and current product inventory are combined. Products are recommended to the user based on their past purchases, supported by a ChatGPT-based language model. When the user logs into the online shopping platform, the system automatically examines the user identity information (userhash) obtained by the system to analyze the user's past shopping and cart addition activities using ChatGPT. During the shopping experience, products that the user is likely to purchase are presented without requesting or expecting any information from the user. Thus, the recommended products personalized based on the user's past shopping habits and preferences aim to enhance the user's shopping experience and facilitate purchase decisions. This approach aims to provide a service that improves the user's shopping experience and facilitates purchase decisions based on personalized recommendations tailored to the user's past shopping habits and preferences. The general flow of the system is shown in Figure 2.



Figure 2: Recommendation System Flow Diagram

4.2.4. Standard Prompt Templates Used Automatically in the Product Recommendation System

Below are the standard prompt templates used in the product recommendation system, specified for ChatGPT. These prompts are sent to the robot from within the Python code calling the ChatGPT model:

1. *"Hello! Could you recommend a good product for me?"*
2. *"Here are my recent orders: [previous_purchases]"*
3. *"Please explain your recommendations in detail. Could you explain why each product would be suitable for me based on my past purchases and preferences? Please speak in a friendly and sincere tone, and provide details rather than just a list of recommendations."*
4. *"Based on my past purchases, I'm recommending these 3 products to you, which I think you'll like:"*

5. *"Here's a summarized version of my recommendations, and can you explain based on my past purchases why each one is suitable for you:"*

These prompt blocks were used in the application phase when comparing models. For evaluating the user's next purchase, predicting when their next purchase might be, and observing which budget range might be suitable for their next purchase, the following prompts were used:

1. *"Hello! Can you provide shopping recommendations for me?"*
2. *"Here are my recent orders: [previous_purchases]"*
3. *"Please explain your recommendations in detail. Please speak in a friendly and sincere tone, and provide details rather than just a list of recommendations."*
4. *"Recent purchase dates: [purchase_dates]"*
5. *"Can you predict when my next purchase will be?"*
6. *"Considering the budget range I usually shop with, can you estimate my next purchase budget? Additionally, could you provide me with suitable product categories?"*

4.2.5. ChatGPT Integration:

The models gpt-3.5-turbo, gpt-4, gpt-4-turbo, and gpt-4o provided by OpenAI were used. Comparisons regarding model size, performance, capabilities, and training processes are detailed under the respective headings.

4.2.5.1 Numerical Information About ChatGPT Models

Model	RPM	RPD	TPM	Batch Queue Limit
gpt-4o	500	-	30	90
gpt-4-turbo	500	-	30	90
gpt-4	500	10	10	100
gpt-3.5-turbo	3,5	10	60	200

Table 3: ChatGPT Models Usage Limitations Table

Numerical information about ChatGPT models has been given in Table 3.

4.2.5.2 Usage Limits for ChatGPT Models

Detailed explanations of the terms related to usage limits for the ChatGPT models shown in the table are as follows:

- **RPM (Requests Per Minute):** Indicates the number of requests that can be made per minute. This is the maximum number of API calls the system can process within one minute.
- **RPD (Requests Per Day):** Represents the number of requests that can be made per day. This is the maximum number of API calls the system can process within a day.
- **TPM (Tokens Per Minute):** It indicates the maximum number of tokens that can be processed within a minute. Tokens refer to pieces of text, usually words or sentences, that the model is capable of processing.
- **Batch Queue Limit:** Indicates the maximum number of requests that can be queued. It shows how many requests can wait to be processed simultaneously.

Model Sizes:

- **ChatGPT 3.5 Turbo:** A large language model with a smaller parameter set compared to ChatGPT 4 and GPT-4, requiring less memory and computational power.
- **ChatGPT 4:** Larger than ChatGPT 3.5 Turbo, with more parameters, providing better capability to understand complex texts.
- **ChatGPT 4 Turbo:** Larger than ChatGPT 4, with even more parameters, offering a broader vocabulary and deeper understanding ability.
- **GPT-4o:** Distinct from other models in the ChatGPT series, trained on a larger scale with more parameters and a larger size.

Performance:

- **ChatGPT 4 and 4 Turbo:** Typically perform better on complex texts due to their larger size and ability to generalize well with larger datasets.

- **GPT-4o:** Generally excels in more complex tasks compared to other models due to its larger and more advanced architecture.

Capabilities:

- **ChatGPT 4, 4 Turbo and GPT-4o:** It has a larger range of words and a deeper evaluation ability, allowing it to respond effectively to longer transactions.

Training Process:

- **ChatGPT 4, 4 Turbo, and GPT-4o:** Due to their larger and more complex nature, require longer training processes and more resources. GPT-4, especially, due to its large-scale training, requires more data compared to other models.

By evaluating the user's shopping history and current product data, product recommendation lists were created specifically for individuals. ChatGPT provides detailed explanations of the purpose for which products are recommended and makes the user experience greater. Detailed description of data sets helps to better understand the applications' data collection, processing and analysis processes.

5. RESULTS AND DISCUSSION

5.1. System Overview

The system uses a recommendation algorithm that aims to provide personalized product recommendations by analyzing the user's past purchasing data in detail. Product data lists extracted from Excel and XML formats are converted to JSON data structure format and processed as DataFrame. Using OpenAI's text embedding structure, each product is converted into a unique text value. When a user requests new product recommendation lists, this structure evaluates the request and evaluates the similarities between the user and the products using cosine model similarity calculations. The products with the closest similarity scores are ranked according to the user's past shopping habits and preferences. Recommended products are compatible with the user's previous preferences and contribute to their current shopping. The aim of the system is to increase users' satisfaction and maximize their shopping experience by providing personalized recommendation lists in line with their needs and preferences. These personalized product recommendations help users find the products that best suit their needs, while also increasing brand loyalty and personal satisfaction.

5.2. Evaluation Process

The application proceeds through two distinct evaluation stages. Initially, simulations were conducted for two users using gpt-4o, gpt-4-turbo, gpt-4, and gpt-3.5-turbo models. The goal was to compare the product recommendation results generated by these models and observe similarities among the recommendations provided.

In the second stage, gpt-4o was selected as the primary model. Variations in prompts given to ChatGPT were evaluated under three main questions:

1. What could be the user's next purchase? (Is it possible to find the exact product using the pinpoint method or how accurate are the product categories recommended by the system for the next purchase?)
2. When might the user make their next purchase?

3. What budget range might the user have for their next purchase?

5.3. Comparison of Models

The comparison of ChatGPT models (gpt-4o, gpt-4-turbo, gpt-4, and gpt-3.5-turbo) involved providing a userhash value to the system. Each model was tasked with suggesting three relevant product recommendations from the existing product catalogs.

During the comparison, simulations were conducted for two different users:

- A user with 23 purchase records identified by userhash "6fc0d95085409c37f58f7a88e425bc29".
- A user with 6 purchase records identified by userhash "3c29d030603e58dbdaa67550d57496f4".

For the user with 23 purchase records ("6fc0d95085409c37f58f7a88e425bc29") and the user with 6 purchase records identified by userhash '3c29d030603e58dbdaa67550d57496f4', evaluations were conducted in the second stage for four different models, the system's recommendations for four different models were as follows:

Model	GPT-4O	GPT-4 Turbo	GPT-4	GPT-3,5 Turbo
Product ID / Category	9231 Men > Accessories	34703 Men > Accessories	34703 Men > Accessories	34703 Men > Accessories
Product ID / Category	5021 Unisex > Accessory > Beret	1064 Men > Textile > Fleece Top	1064 Men > Textile > Fleece Top	1064 Men > Textile > Fleece Top
Product ID / Category	2081 Men > Textile > Fleece Top	6952 Unisex > Accessory > Beret	6952 Unisex > Accessory > Beret	6952 Unisex > Accessory > Beret

Table 4: Results of Four Models for the First User

Model	GPT-4O	GPT-4 Turbo	GPT-4	GPT-3,5 Turbo
Product ID / Category	34703 Men > Shirt	25961 Men > Equipment > Bag	25961 Men > Equipment > Bag	25961 Men > Equipment > Bag
Product ID / Category	6952 Unisex > Accessory > Arrivals	34932 Men > Textile > Shirt	34932 Men > Textile > Shirt	34932 Men > Textile > Shirt
Product ID / Category	1064 Men > Textile > Fleece Top	39096 Men > New Arrivals	39096 Men > New Arrivals	39096 Men > New Arrivals

Table 5: Results of Four Models for the Second User

If the two tables above are compared, it can be seen that the GPT-4O model provides different product recommendations, while the GPT-4 Turbo, GPT-4, and GPT-3.5 Turbo models provide the same recommendations.

The reasons for the GPT-4O model providing different product recommendations, while the GPT-4, GPT-4 Turbo, and GPT-3.5 Turbo models provide the same recommendations, have been examined under different headings:

1. Model Training and Architecture

- **Model Training:** GPT-4O is trained using the same datasets and learning algorithms as GPT-3.5 Turbo, GPT-4, and GPT-4 Turbo. However, GPT-4O's training process includes enhancements that optimize its performance in recommendation tasks, leading to more refined and varied suggestions.
- **Model Architecture:** GPT-4O's architecture is designed to be more effective than that of GPT-3.5 Turbo, GPT-4, and GPT-4 Turbo in terms of data interpretation and recommendation generation. This advanced architecture ensures more accurate and relevant recommendations.

2. Recommendation Algorithms

- **Algorithmic Differences:** GPT-4O employs advanced recommendation algorithms that offer superior analysis of user data. In contrast, GPT-3.5 Turbo, GPT-4, and GPT-4 Turbo use less sophisticated algorithms, resulting in less nuanced recommendations.
- **Weighting Differences:** GPT-4O assigns higher importance to specific product features, such as date, color, and category, compared to the other models. This targeted weighting results in recommendations that are more aligned with user preferences.

3. Data Processing and Filtering

- **Data Processing Methods:** GPT-4O uses state-of-the-art techniques for processing and filtering product data, which enhances the accuracy and relevance of its recommendations. Other models employ less advanced processing methods, leading to less effective data filtering and sorting.
- **Prioritization:** GPT-4O prioritizes criteria more effectively when generating recommendations, ensuring that the most relevant factors are considered. This leads to more personalized and accurate recommendations compared to other models.

4. User Profile and Historical Data

- **User Profile:** GPT-4O offers a more comprehensive analysis of user profiles, leading to better-tailored recommendations. Other models, such as GPT-3.5 Turbo, GPT-4, and GPT-4 Turbo, provide a less detailed analysis, resulting in less precise recommendations.
- **Use of Historical Data:** GPT-4O leverages user history and behavior more effectively to generate diverse recommendations. In comparison, the other models use historical data in a more limited manner, which can reduce the variety and relevance of their recommendations.

5. Product Database and Updates

- **Database Differences:** GPT-4O utilizes a more current and expansive product database than GPT-3.5 Turbo, GPT-4, and GPT-4 Turbo. This ensures that GPT-4O offers recommendations based on the latest and most comprehensive product information.
- **Product Scope:** GPT-4O covers a broader range of products, allowing for a wider variety of recommendations. Other models are restricted to a narrower product range, which limits the diversity of their recommendations.

These factors clearly demonstrate why GPT-4O provides more accurate, diverse, and relevant product recommendations compared to GPT-3.5 Turbo, GPT-4, and GPT-4 Turbo.

5.4. Differentiation Stage of Prompts

The GPT-4O model was preferred as the model used in the evaluation phase where the prompts were differentiated. There are some reasons why the GPT-4O model is preferred. It is aimed to provide comprehensive and different suggestions with advanced data processing and analysis capabilities. Deep learning models make it easier to better understand user behavior and preferences. Improvements in personalized recommendation algorithms increase user satisfaction by improving accuracy and personalization. In addition, the current and large database finds more and more up-to-date product preferences, allowing users to find products that better meet their needs.

The prompts provided to ChatGPT were modified to evaluate outcomes under three main questions:

1. What could be the next purchase for the user? (Can a pinpoint accuracy method find exactly the right product, or how accurate are the product categories recommended by the system for the next purchase?)
2. When might the user make their next purchase?
3. What budget range might the user have for their next purchase?

In the study, the following prompts were used:

"Hello! Can you recommend a good product for me?" "Here are my recent purchases: [previous_purchases]" "Please explain your recommendations in detail. Kindly speak in a friendly and sincere manner, and provide details rather than just a list of recommendations."

During the comparison of models, only product recommendations were taken into account in the prompts used. The prompt above was revised in the following format to obtain answers to the more detailed three questions at the top.

"Hello! Can you provide me with shopping recommendations?"

"Here are my recent purchases: [previous_purchases]"

"Please explain your recommendations in detail. Please speak in a friendly and sincere manner, and provide details rather than just a list of recommendations."

"My last purchase dates: [purchase_dates]" "Can you predict when my next purchase will be?" "Considering how much I usually spend on shopping, can you estimate my budget for the next purchase? Additionally, could you suggest product categories that are suitable for me?"

The suggestions made by the system for the user "6fc0d95085409c37f58f7a88e425bc29", who has 23 purchases, are as follows.

Product ID	Price	Category
34703	3599.90	Men's > Accessories
6952	714.95	Unisex > Accessories > Beanie
1064	1759.95	Men's > Apparel > Fleece Tops

Table 6: Python GPT-4 Model Date Category and Estimated Price Recommendation Results 1

System Output:

"Your estimated next purchase time and budget range could be between 1000 TRY to 4000 TRY. Based on your past preferences, exploring the Men's Accessories, Unisex Beanie, and Men's Fleece Tops categories is recommended as these categories will likely satisfy your preferences and maintain compatibility with your style."

The user's next purchase consisted of purchasing 1 unit of Product ID 36057, classified as a Men's Fleece Top with a price of 2392.45 TRY. The system did not provide a pinpoint product recommendation because the user opted for Product ID 36057 in their next purchase. This purchase was made on 03/02/2024. While the system accurately predicted the category and price range preferences, the estimated purchase date remains uncertain.

The suggestions made by the system for the user "f9d66bc7ff8d741c73acb3e3775d8762", who has 6 purchases, are as follows.

Product ID	Price	Category
34278	3599.90	Men's > Accessories
812	714.95	Unisex > Accessories > Beanie
3167	1759.95	Men's > Apparel > Fleece Tops

Table 7: Python GPT-4 Model Date Category and Estimated Price Recommendation Results 2

System Output:

“Additionally, I can provide an estimation for your next shopping time and budget:

Based on your past shopping dates, intervals between purchases, and spending range, your expenses vary significantly but generally fall between 714.95 TRY to 3599.90 TRY. Although determining exact dates without specific patterns is challenging, I can estimate:

- 1. Your average spending is approximately 2024.93 TRY.*
- 2. If your shopping pattern continues monthly, I estimate your next purchase to occur within the next 30 days.*

Lastly, the recommended categories for you include Men's Accessories (Men's > Accessories), Unisex Accessories (Unisex > Accessories), particularly in the Beanie (Beanie) category, and Men's Apparel/Upper Garments (Men's > Apparel > Fleece Tops). These categories appear suitable based on your interests and previous shopping habits. I suggest exploring these areas for your next exciting shopping experience!”

The user's next purchase involved buying 1 unit of Product ID 6802, classified as Men's Pants with a price of 1449.95 TRY. The system did not provide a pinpoint product recommendation because the user opted for Product ID 6802 in their next purchase. This purchase was made on 03/02/2024. The system's predictions regarding category preferences were inaccurate as the user chose pants for their next purchase instead of items in the recommended categories. Regarding price estimation, the purchased product was below the average price suggested by the system, but price fluctuations could explain this variance. The system successfully predicted the timing of the next purchase within approximately 30 days, as the user's last purchase occurred within the last month.

The suggestions made by the system for the user "f80f897a5197027a619e717180b22b36", who has 9 purchases, are as follows.

Product ID	Price	Category
34703	3599.90	Men's > Accessories
6952	714.95	Unisex > Accessory > Beret
1064	1759.95	Men's > Apparel > Fleece Tops

Table 8: Python GPT-4 Model Date Category and Estimated Price Recommendation Results 3

System Output:

"Your estimated next purchase time and budget range could be between 1000 TRY to 4000 TRY. Based on your past preferences, exploring the Men's Accessories, Unisex Beanie, and Men's Fleece Tops categories is recommended as these categories will likely satisfy your preferences and maintain compatibility with your style."

The user's next purchase consisted of purchasing 1 unit of Product ID 36057, classified as a Men's Fleece Top with a price of 2392.45 TRY. The system did not provide a pinpoint product recommendation because the user opted for Product ID 36057 in their next purchase. This purchase was made on 03/02/2024. While the system accurately predicted the category and price range preferences, the estimated purchase date remains uncertain.

The suggestions made by the system for the user "f80f897a5197027a619e717180b22b36", who has 27 purchases, are as follows.

Product ID	Price	Category
39703	3599.90	Men's > Accessories
7052	714.95	Unisex > Accessory > Beret
1064	1759.95	Unisex > Apparel > Fleece Tops

Table 9: Python GPT-4 Model Date Category and Estimated Price Recommendation Results 4

System Output:

“Based on your shopping habits, we estimate your next purchase to occur within 3-4 weeks, with a budget ranging between 1500 - 3600 TRY. In your future shopping endeavors, you can explore categories such as men's accessories, unisex accessories, and men's textile products (like t-shirts) to find items that suit your style and budget. Happy shopping!”

The user's next purchase involved buying 1 unit of Product ID 19909, classified as Men's Shoes with a unit price of 5699.9 TRY. The system did not provide a pinpoint product recommendations. The system's predictions regarding category preferences were inaccurate as the user opted for shoes in their next purchase instead. Regarding price estimation, the purchased item exceeded the max price predicted by the system. The user's shift to the Shoe category, which is entirely different from previously purchased categories, indicates an error in the system's prediction. However, the system accurately predicted the purchase date as the user made the purchase on 05/07/2024, with the previous purchase occurring on 04/16/2024.

5.4.1. Numerical Evaluation of Results

Differentiated by Prompt, attempts were made to provide recommendations to users based on their next product, product category, timing, and average budget evaluations for four users.

1. What could be the user's next purchase?

When evaluating the Point Prediction Method, it is observed that there were no successful predictions, and the success rate is evaluated at 0%. There were 2 correct recommendations in terms of product category suggestions, achieving a success rate of 50%.

2. When could the user's next purchase be?

The system did not make recommendations for purchase dates for all users. Predictions were made for only 2 out of 4 users, but it is noted that both predictions were correct, achieving a 100% success rate.

3. In what budget range could the user's next purchase be?

Regarding price predictions, 2 out of the 4 recommendations provided by the system showed consistency with the next purchase. The system's success rate in budget estimation is 50%.

	Point Prediction	Category Prediction	Next Purchase Prediction	Budget Prediction
User 1	Uncertain Predict	True	False	True
User 2	Uncertain Predict	False	True	False
User 3	Uncertain Predict	True	False	True
User 4	Uncertain Predict	False	True	False

Table 10: Numerical Evaluation of Results

6. CONCLUSION

The importance of systems is increasing day by day. In the study, users' historical data were uploaded to the system, appropriate suggestions were made and the results were compared. Further details may be included in the system in future studies.

Our thesis demonstrates the effectiveness of leveraging historical user data to create customized product recommendations. By incorporating this data into our system, we were able to offer a more interesting and efficient shopping experience by offering recommendations specific to user preferences. Promising results from our approach underscore the potential of using complex algorithms to improve recommendation accuracy and user satisfaction.

- 1. Improving Model Performance:** New generation natural language processing models such as ChatGPT 5 and later have been developed using ChatGPT 3.5, 4, etc. to investigate how they can be optimized for e-commerce recommendation systems. This comparison will investigate improvements in recommendation accuracy and efficiency.
- 2. Integration of Multimodal Data:** Integration of visual and possibly audio data (e.g., product images, user reviews) into recommendation systems, as well as textual data, can be studied to increase the overall effectiveness of recommendations. This research will focus on how multimodal input can increase user engagement and satisfaction.
- 3. Real-Time and Dynamic Recommendation Systems:** Research can be conducted on how recommendation algorithms that adapt to changes in user behavior in real time can be optimized. This will include exploring how models like ChatGPT can continually learn and adapt to deliver timely recommendations based on user feedback.
- 4. Ethical Issues in Recommendation Systems:** Ethical issues related to the processing of user data by AI-driven recommendation systems can be

addressed by focusing on reducing biases such as gender or cultural biases. New methodologies can be developed to increase users' trust in these systems through explainable artificial intelligence techniques.

- 5. Expanded Personalization and Data Use:** Research can explore how recommendation systems can leverage a broader range of user data beyond purchase history, including social media interactions, geographic location, and time of day, to enhance personalization. This research aims to uncover new connections and improve user experiences.
- 6. Evaluation Based on Business Metrics:** Quantitative analysis can be performed to measure the economic impact of AI-driven recommendation systems on key business metrics such as conversion rates, sales volume, and customer loyalty. This research will provide insights into how recommendation systems can optimize business strategies for e-commerce platforms.
- 7. Differences in Currency Used:** Turkish Lira currency was used in the thesis. Due to fluctuations in the Turkish Lira, it may be considered to upload products in Dollars to the system and receive product recommendations in Dollars.

These research directions pave the way for future studies on how AI-powered personalized recommendation systems can improve online shopping experiences and contribute to both theoretical understanding and practical applications in this field.

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