An E-Commerce Recommendation Systems Based on Analysis of Consumer Behavior Models

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Abstract

The article presents some models and strategies of consumer behavior in electronic commerce systems. An analysis of e-commerce recommender systems was also carried out, including context-aware recommender systems on the example of the analysis of regions of Ukraine and weather conditions, etc. The core of the novelty of the research is primarily related to hybrid behavioral models, personalization, contextual recommendations, especially integrating contextual information, such as location, time of day, or user intent, evaluation metrics, etc. The impact of machine learning and artificial intelligence on e-commerce recommender systems and e-commerce systems in general is also explored. The article also presents the microservice architecture of an electronic store with recommender system API. The architecture includes several key components, such as client-side APIs for managing orders, products and carts, services for processing customer requests and interacting with databases, and data processing technology using artificial intelligence.

Keywords

E-commerce, consumer behavior model, *e*-commerce recommendation systems, adaptive user profiling

1. Introduction

The widespread popularity of the Internet and the implementation of web technologies worldwide have led to an increasing number of people abandoning traditional shopping methods and opting for online payments and purchases. As globalization, informatization, and computerization continue to advance, commercial transactions are increasingly taking place on specialized web pages such as online stores, e-commerce platforms, online showcases, online auctions, online trading platforms, etc.

All of these are participants in e-commerce ecosystems. An e-commerce ecosystem can be understood as an area of activity where buyers and producers play complementary roles. Components of an e-commerce ecosystem typically include: customers, sellers, online marketplace, online payment system, logistics, marketing, data analysis, etc. Let's explore the essence of consumer behavior models and modern approaches in using recommender systems of e-commerce platforms.

Consumer behavior models play a crucial role in modern e-commerce systems. These models help companies understand how consumers make decisions and interact with online platforms, enabling them to adapt their products, services, and marketing strategies according to consumer needs. One of the most widely used consumer behavior models is the buyer decision-making process model, which consists of five stages: 1) problem recognition, 2) information search, 3) evaluation of alternatives, 4) purchase decision, and 5) post- purchase evaluation and follow-up. E-commerce systems can use this

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model to guide consumers through each stage of the decision-making process, providing relevant information and recommendations at each step.

Another important model is the consumer value hierarchy, which defines various levels of value that consumers seek in a product or service, such as functional, emotional, and social benefits. E-commerce systems can employ this model to understand the values consumers prioritize and accordingly develop their products and services. Additionally, e-commerce systems can leverage behavioral economics theories to influence consumer behavior, such as nudging methods to encourage consumers to make a specific choice or increase their willingness to pay.

Overall, models of consumer behavior are essential for modern e-commerce systems to optimize their offerings, user experiences, and sales conversions by understanding how consumers think, feel, and behave when making purchasing.

The specificity of e-commerce means that traditional models of consumer behavior in a regular store cannot be used when buying online. This is primarily due to the absence of physical attributes of the store, such as the cleanliness of the goods and the trading floor, convenience of entering and store location, and emotional and psychological factors that affect subjective consumer opinions. Additionally, trust factors related to e-stores, products, and transactions are of utmost importance in e-commerce. As a result, consumer behavior models have undergone significant changes. The emergence and spread of the Internet cannot be viewed in isolation, and the models discussed below are a synthesis of offline and online behavior.

M. Wenzl's research identified significant e-commerce trends that drive online consumer behavior. Convenience is a top priority, and online shoppers seek easy access across all devices, looking for a seamless transfer between devices throughout their buying journey. Access to omnichannel shopping, with multiple technology options, engages consumers in an ‘always-on’ shopping experience, and most consumers now shop while multitasking. Effortless payment and fast and reliable delivery are also must-have factors when shopping online [1].

In [2] authors explore the strategies that online shop owners can use to stimulate customers to explore new products, suggesting that a combination of surprise, novelty, and interactivity can lead to more exploratory behavior. An integrated model of e-service quality, customer value, and switching costs to enhance consumer engagement in e-commerce websites, finding that these factors positively impact customer engagement proposed in [3]. In [4] investigated the decision-making processes underlying consumers' choices between same-day and next-day delivery in online shopping, finding that factors such as product type, urgency, and situational characteristics play a role in this decision.

The concept of digital affordances in the context of business-to-consumer e-commerce, highlighting the importance of considering consumers' perceptions of technology's capabilities when designing digital platforms proposed in [5]. Also, in [6] was research the design of recommendation systems on e-commerce platforms with multiple objectives, proposing a multi-objective optimization model that considers the trade-offs between relevance, diversity, and novelty.

Overall, e-commerce research helps understand how to enhance the online shopping experience for consumers, create more effective digital marketing strategies, and develop relevant recommender systems for e-commerce. This is important as online commerce continues to grow and gain more popularity. Technological approaches to understanding consumer behavior in e-commerce, such as the utilization of technology adoption models and impulse buying models have been discussed in [7-10].

Many researchers study issues related to consumer behavior in e-commerce and propose various models and frameworks for analyzing and predicting consumer behavior. Examples include a model for analyzing consumer behavior in e-commerce considering service quality [11], a model for evaluating the role of customer behavior history, product classification, and pricing in the success of recommendation systems in e-commerce [12], a model for constructing hierarchical polarization characteristics in conjunction with consumer behavior in social e-commerce [13], a framework for evaluating online markets considering trust and sustainability to predict customer behavior in e-commerce [14], as well as a model that combines virtual reality technology and gamification to enhance the consumer experience in tourism e-commerce [15]. These models cover different aspects of consumer behavior in e-commerce. How-ever, to create a comprehensive understanding, it is necessary to consider the dynamics of digital markets and trends in their development, as well as important tools for supporting and advancing e-commerce, such as recommendation systems. Recommender system of e-commerce recommender system of e-commerce systems are algorithms and techniques used in online shopping platforms to suggest relevant and personalized product recommendations to individual users. These systems aim to enhance the user experience, increase customer engagement, and ultimately improve conversion rates and sales. The primary goal of e-commerce recommender systems is to present users with a set of items that match their preferences, interests, and past behavior.

These recommendations can be based on various data sources, including user profiles, browsing history, purchase history, demographic information, and explicit feedback (such as ratings and reviews). The system analyzes this data to identify patterns, similarities, and correlations among users and items. Personalized recommendation refers to the practice of suggesting products, services, or content to individuals based on their unique preferences, interests, and past behaviors. It aims to provide a tailored and relevant experience to each user, increasing engagement, satisfaction, and ultimately driving sales in the case of e-commerce. Implicit data, such as click pat-terns, browsing history, and time spent on different pages, can also be collected; data collection - the system collects data on user interactions, such as product views, purchases, ratings, and reviews.

This data is used to create a user profile or model that captures the user's preferences and behavior; real-time adaptation - recommendation systems often update their recommendations in real time to adapt to the user's changing preferences and behaviors. This can be achieved through continuous monitoring and analysis of user interactions. It's important to note that implementing personalized recommendation systems requires handling user data and privacy concerns responsibly. Companies should be transparent about data usage, provide options for users to control their privacy set-tings, and adhere to relevant data protection regulations.

Overall, personalized recommendation systems in e-commerce leverage user data and algorithms to provide tailored product suggestions, enhancing the user experience and driving engagement and sales. So, the objectives of this article are to investigate and analyze consumer behavior models and recommendation systems in e-commerce within the dynamic digital environment of an ever-evolving digital society. In this article, we will discuss the impact of artificial intelligence technologies for data processing and machine learning in developing consumer behavior models and recommendation systems in modern e-commerce systems.

Aspects of novelty in this research cover areas such as consumer behavior patterns, data analysis techniques, and algorithms with personalization and customization. These models are based on factors such as browsing history, past purchases, social interactions, demographics, personalization, etc.

The article proposes hybrid methods of data analysis to obtain meaningful information from consumer behavior data. This involved applying machine learning, data mining, and statistical techniques to identify patterns, trends, and correlations that can be used to provide accurate recommendations. These algorithms can combine different techniques such as collaborative filtering, content-based filtering or hybrid approaches to create personalized and relevant product recommendations for individual users. This may to help explore ways to tailor recommendations based on individual preferences, needs and context, providing a more tailored and satisfying user experience. This may include measuring user satisfaction, conversion rates, click-through rates, or other relevant metrics to validate the impact of proposed models and algorithms.

Overall, the novelty of the study is the combination of consumer behavior analysis, data mining techniques and recommendation algorithms to create e-commerce recommendation system.

2. Materials and Methods

A qualitative research approach was employed in the study, which involved the analysis and synthesis of data and a systematic approach. The results were then used to draw conclusions about the significance of identified factors for the successful functioning of e-commerce recommender systems and how consumer behavior models can be utilized to create effective digital marketing strategies and personalized customer strategies. Overall, the materials and methods used in this research aimed to provide a comprehensive understanding of key factors contributing to the success of e-commerce systems, including descriptions of consumer behavior models and e-commerce recommender systems.

2.1. Models of Customer Behavior

There are many models that take into account the motives for product selection, the level of awareness and independence in choice, the level of consumer satisfaction with the product, and the direction and possibility of influencing consumer choice through marketing and advertising stimuli. There are also other well-known consumer behavior models.

The rational model corresponds to the concept of an “economic man”, rationalizing their actions on the path to personal gain. The irrational consumption model is based on behaviorism with the principle of “stimulus-response”: if the emotional attractiveness of a product is presented to the consumer for a sufficient amount of time in a comprehensible form, they will indeed begin to experience positive emotions from its acquisition.

The motivated consumer model requires understanding the consumer's motives, reasons, and the content of their attitudes in order to find means of stimulating their choice. The conformist consumer model is an evolution of the previous model. In a consumption-driven society, the dominant attitudes of individuals become those related to their desire to conform to the norms of social groups they want to belong to. It forms their social identity through a specific consumer basket containing goods and services that meet the group's standards.

The consumerist consumption model revolves around the idea of consumption itself. For individuals in this model, the mere opportunity to consume becomes a significant symbol of achievement and life fulfillment. The requirements that this model imposes on consumer behavior are high - these are the requirements of environmental friendliness, safety, ethical purity of both the products themselves and manufacturing companies. In the era of digital transformation, models of the information consumer have emerged, whose decisions about choosing a product or service are completely tied to the electronic devices that they actively use when choosing in digital markets. And this model has received significant distribution [16-17]. In 2018, Forbes noted the growing popularity of the “Research Online / Purchase Offline” model: people are increasingly studying offers on the Internet in detail, com-paring different brands, and only then make a purchase decision [18].

A significant limitation in this model is that sometimes it is quite difficult for small and medium-sized stores to track whether the study of a product and brand on the Internet really led to a further purchase in an offline store. However, this consumer decision model should always be kept in mind when branded advertising is launched on the Internet. Thus, you can understand how a launched advertising campaign affects offline sales.

In addition to the behavior models described above, there is an integral model of consumer trust according to the statement of L. Chong and a conceptual model of Citrine. L. Chong's approach is to identify four reliability factors for online sellers: perceived integrity, competence, security control and privacy control. The main focus of the Citrine model is the behavior of the consumer, which depends only on the level of the consumer's knowledge of the Internet and computers in general, which is a primary for the Internet consumer, indispensable condition and is taken into account initially.

Must remember, with the spread of Covid-19 some of the behavior models have ceased to be relevant, while others have succumbed to significant changes. The coronavirus has changed consumer behavior online. According to the [19] re-search, 18% of users began to consume video content more often, 12% of people began to listen to music and radio more often, 15% of respondents began to use online shopping services more often, and 76% of respondents noted, which changed the habits associated with hobbies and content consumption after the introduction of the forced self-isolation regime. Therefore, in the digital world, behavior models can be influenced by factors that have an external impact on the user of the e-trade and can significantly change his behavior.

So, let's summarize some strategies of consumer behavior. Buyers in e-commerce employ various personal strategies to enhance their online shopping experiences and achieve their desired outcomes. There are some common strategies employed by e-commerce buyers. This in particular,

1. Research and comparison, buyers often conduct thorough research on products or services they intend to purchase. They compare prices, features, reviews, and ratings across multiple e-commerce platforms to find the best option.
2. Buyers rely on customer reviews and ratings to gain in-sights into the quality, reliability, and performance of products. Positive reviews and high ratings can instill confidence in a purchase, while negative feedback may lead buyers to consider alternative options.
3. Buyers often use wishlists or add items to their carts to save products they are interested in. This allows them to review and compare options before making a final decision, and it also enables them to track price changes or availability updates.

4. Buyers may set up price alerts or use price tracking tools. These notifications inform them when the desired item reaches a specific price point, helping them make cost-effective purchases.

5. Buyers actively search for discount codes, coupons, or promotional offers to reduce the overall cost of their purchases. They may follow brands or retailers on social media, subscribe to newsletters, or use dedicated coupon websites to find exclusive deal.

6. Security is a crucial concern in e-commerce. Buyers prioritize platforms that offer secure payment options, such as encrypted transactions or trusted third-party payment processors, to safeguard their personal and financial information.

7. Buyers review the re-turn and refund policies of the e-commerce platform or individual seller. They seek hassle-free return options, reasonable refund terms, and clear instructions in case the product does not meet their expectations.

8. When buyers have questions, concerns, or require additional information, they may reach out to customer support via live chat (chat-bot on base AI), email, or phone. Prompt and helpful customer service can positively influence their decision to proceed with a purchase.

9. Buyers keep track of the shipping status of their orders by utilizing tracking numbers or delivery notifications. This allows them to estimate delivery times, plan accordingly, and ensure the package arrives in a timely manner.

10. After completing a purchase, buyers often share their feedback and experiences through product reviews or ratings. This not only helps other buyers make informed decisions but also provides valuable insights to sellers and platforms, etc.

These personal strategies may vary from buyer to buyer based on their preferences, ages, priorities, and previous experiences in e-commerce activities.

Therefore, in the consumer behavior model presented by us, we have built upon the well-known eCDP (Electronic Consumer Decision Process Model), which examines five stages of decision-making: problem recognition, information search, alternative evaluation, purchase, and outcomes [20]. This model is widely recognized and extensively used in consumer behavior research in e-commerce. It provides a comprehensive framework that describes the fundamental stages of consumer decision-making in online purchases. The eCDP model offers insights into the key factors influencing consumer decision-making and can serve as a foundation for developing digital marketing strategies and personalized approaches for customers. Optimizing this model allows us to gain a deeper understanding of how consumers make decisions in online purchases and how recommendation systems can be tailored for optimal consumer impact, Figure 1.

So, at the first stage of "problem recognition" in accordance with the well-known eCDP model, we propose incorporating pseudo-identification of users (building a data-base of anonymous users and rules based on their presence in web applications). The main advantages of this approach lie in the fact that the identification model of anonymous users in software products can be utilized as a dynamic identifier for automatically adapting the interface of an online store to the identified user [21].

2.2. Analysis of recommender systems of e-commerce

A recommendation system is a tool that uses a series of algorithms, data analysis and artificial intelligence (AI) to make recommendations online. Recommender systems are used by e-commerce sites to suggest products to their customers. As mentioned above recommender systems in e-commerce are information filtering systems that provide personalized recommendations to users based on their preferences, behaviors, and past interactions with the platform or similar users. These systems are designed to help users discover relevant products or services that they might be interested in, thereby improving their shopping experience and increasing engagement and sales for e-commerce businesses.

The *importance of recommender systems in driving sales and enhancing user experience in e-commerce*. Recommender systems in e-commerce play a crucial role in boosting sales and improving user experience. These systems offer personalized recommendations based on user behavior and preferences, leading to increased sales and customer satisfaction. By suggesting relevant products, they enhance engagement and encourage repeat visits. Moreover, recommender systems excel at cross-selling and upselling strategies, increasing the average order value. In platforms with vast catalogs, they assist users in discovering desired items, ultimately driving more sales. Overall, effective recommender systems provide a competitive edge, attracting new customers and retaining existing ones, resulting in enhanced user experience and increased revenue.

The different types of recommender systems used in e-commerce. In e-commerce, there are several types of recommender systems commonly used to provide personalized recommendations to users. These systems leverage various techniques and algorithms to analyze user behavior, preferences, and item characteristics.

Let's note there are several types of e-commerce recommender systems.

Content-based filtering recommends items to users based on item characteristics and user preferences.

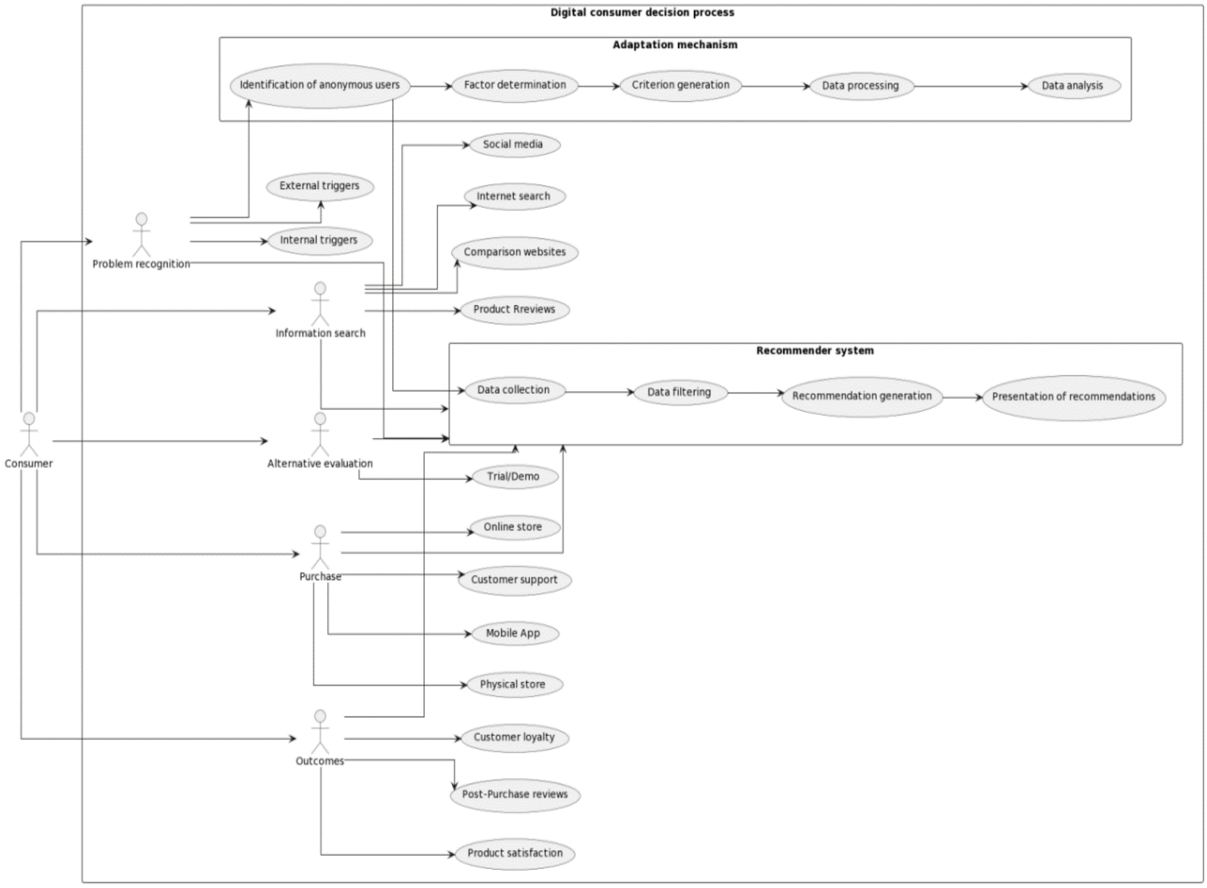

Figure 1: Model of customer behavior with adaptation mechanism and recommender system block

User-based collaborative filtering. It finds users who have similar preferences to the target user and recommends items that those similar users have liked or purchased. Item-based collaborative filtering: it identifies similar items based on user preferences and recommends items that are similar to the ones the user has already interacted with.

Hybrid recommender systems. These systems combine multiple recommendation techniques, such as content-based filtering and collaborative filtering, to provide more accurate and diverse recommendations. Hybrid approaches aim to leverage the strengths of different methods and overcome their individual limitations. For such purposes, approaches based on machine learning (ML) are also appropriate.

Reinforcement learning uses ML algorithms to learn user preferences and optimize recommendations over time. It involves continually adapting and refining the recommendation strategy based on user feedback and interactions.

Knowledge-based recommender systems use domain-specific knowledge and rules to generate recommendations.

Demographic-based filtering recommends items based on demographic information such as age, gender, location, or occupation.

Context-aware recommender systems consider contextual factors like time, location, and user situations for personalized recommendations. Data enrichment can include a variety of parameters that provide additional information about the context of transactions and the impact of external factors on consumers:

- Geographical data, meaning the location of transactions, including city, country, address, latitude and longitude, allows you to understand how regional characteristics affect purchases.
- Temporal data, such as date and time of transactions, helps identify trends across different time periods.
- Weather conditions such as temperature, humidity, wind speed, precipitation, visibility and cloud cover reveal the impact of weather on consumers and their purchasing decisions.
- The phases of the moon indicate the possible impact of cyclical changes on consumption. Environmental data, such as air pollution levels, water quality, and other environmental factors, can influence consumer choices.
- Social data, such as demographics, information about local events or celebrations, consumer trends and sentiments, helps in understanding the social influence on purchases.

Enriching data with these parameters provides more detailed and contextual in-formation about transactions, which helps improve marketing strategies, personalize offers and improve customer interactions in e-commerce. Environmental data enrichment is an important step in gaining a more complete and contextual understanding of e-commerce transactions. To perform the enrichment, we use the location and time from each transaction in the dataset.

Enriching the data environment also allows you to study correlations between different parameters and transaction data. For example, you can analyze the correlation between geographic data, such as the location of transactions, and the level of spending or the popularity of a certain product in a certain region. This makes it possible to identify connections between the location of consumers and their purchases.

Correlation between time data and purchases can also be explored. For example, you can study whether there is a relationship between a date or a day of the week and the volume of sales of a certain product or service. This can help identify seasonal trends, popularity on certain days or times of day, and the impact of holidays or special events on consumption. Correlation can also be studied between weather conditions and shopping. For example, research shows that weather factors such as temperature or precipitation can influence the consumption of certain goods or services. This makes it possible to forecast demand depending on weather conditions and take this into account when developing marketing strategies.

Additionally, social data such as demographics or trends can be used to explore correlations between these factors and purchases. For example, it is possible to study whether there is a relationship between the age of consumers and their preferences for goods or services. This helps to make more informed decisions about the target audience and to set up a more effective advertising strategy. Analyzing correlations between different data parameters can also help reveal more complex relationships and trends. For example, correlations between geographic data, social characteristics, and purchases can be studied to gain a deeper understanding of the influence of cultural factors on consumption.

It is important to note that correlation does not always mean causation between variables. It indicates a statistical relationship between them, but does not necessarily indicate the cause or direction of this relationship. Data enrichment and analysis of correlations between various parameters allow increasing the level of understanding and prediction of consumer behavior. This provides opportunities to develop more effective marketing strategies personalize offers and improve customer interaction in e-commerce. An analysis was conducted by region in Ukraine, and the following parameters were determined: Average Purchase Value (APV), Average Purchase Frequency Rate (AP FR), Customer Value (CV). The study showed interesting results indicating different levels of customer value in different regions of Ukraine (Table 1).

Firstly, it was established that the highest lifetime customer value is observed in Odesa. This suggests that customers from this region are more likely to make repeat purchases, remain interested in the brand, and spend more on online shopping. On the other hand, the lowest customer lifetime value was found in the Volyn region. This may indicate less activity and less frequent purchases by customers from that region, or other factors affecting their value to the business.

Analyzing average purchase value and purchase frequency will also allow companies to gain insight into customer spending levels and customer activity across regions. Based on this data, pricing strategies, bonus programs and other marketing initiatives can be developed to attract new customers and retain existing ones.

Table 1
Analysis by regions of Ukraine.

Region of Ukraine	APV	AP FR	CV
Odesa region	622.26	2.69	1670.88
Zaporizhia region	574.86	2.88	1652.94
Khmelnytsky region	704.58	2.32	1632.19
Kyiv region	608.45	2.64	1604.21
Donetsk region	641.18	2.45	1573.35
Kharkiv region	583.42	2.67	1558.51
Chernivtsi region	596.87	2.61	1558.14
Dnipropetrovsk region	606.99	2.55	1550.05
Kirovohrad region	611.29	2.51	1534.99
Luhansk region	640.54	2.35	1504.36
Mykolaiv region	600.74	2.46	1479.63
Ivano-Frankivsk region	600.60	2.44	1466.63
Ternopil region	630.96	2.32	1463.00
Rivne region	550.27	2.62	1441.66
Poltava region	598.11	2.41	1439.70
Zakarpattia region	634.79	2.25	1429.97
Zhytomyr region	595.70	2.31	1373.47
Kherson region	567.06	2.41	1367.96
Lviv region	581.70	2.34	1360.38
Vinnytsia region	636.21	2.13	1357.43
Cherkasy region	590.14	2.12	1249.69
Sumy region	561.29	2.09	1171.68
Chernihiv region	566.39	2.06	1168.19
Volyn region	594.89	1.94	1154.48

In addition, the analysis of the average purchase price and the frequency of purchases allows to reveal the peculiarities of consumption in different regions. For example, if the average purchase price is higher in one region, this may indicate the presence of customers with greater financial capabilities or the presence of premium market segments. Such data can become the basis for the development of special promotions or offers for target audiences.

The analysis showed that customer engagement increases by 14 percent during rain compared to other weather conditions. This means that under the influence of rain, customers are more likely to interact with businesses and make purchases.

Such analysis results indicate the importance of taking into account weather conditions and time of day when developing marketing strategies. Businesses can use this information to target rain and nighttime efforts by offering special offers, discounts or promotions that will attract more customers and drive purchases. An analysis of attracting new regular customers based on external factors such as time of day, weather conditions and atmospheric pressure was carried out. During the analysis, it was found that the most effective factors of attraction are rain and night time (Table 2).

E-commerce recommender systems face challenges like the cold start problem, scalability, data scarcity, and lack of contextual consideration. They tend to lack diversity, serendipity, and transparency while struggling to adapt to dynamic user preferences and address privacy concerns. Advanced recommender systems use hybrid approaches, context-aware recommendation, and deep learning techniques to overcome these limitations.

ML and AI have greatly influenced recommender systems for e-commerce. Advancements in ML and AI have had a significant impact on recommender systems in the field of e-commerce. Overall, advancements in ML and AI have revolutionized recommender systems in e-commerce, enabling them to deliver more accurate, personalized, and context-aware recommendations. Modern recommender systems leverage techniques like deep learning and natural language processing (NLP) in various ways to improve their recommendations. Some common approaches we are proposed the best known.

Table 2

Analysis of weather conditions

Weather conditions	Variance
Snow	-1.00%
Partially cloudy	2.90%
Rain	14.20%
Clear	-3.60%
Overcast	-12.40%

Collaborative filtering with deep learning – deep learning models, such as neural networks, can be used to learn latent representations of users and items from historical user-item interactions. These models can capture complex patterns and relationships in the data, enabling more accurate recommendations. Techniques like matrix factorization and autoencoders are often employed for collaborative filtering using deep learning.

Content-based filtering with NLP – NLP techniques are used to process and understand the textual content associated with items or user preferences. Natural language processing algorithms can analyze the text to extract features, such as keywords, topics, sentiment, or semantic meaning. These features are then used to build item profiles or user profiles, enabling content-based filtering. NLP techniques like text classification, named entity recognition, and sentiment analysis can be used for this purpose.

Neural embedding – deep learning models can learn dense vector representations, known as embedding, for items and users. These embedding capture the underlying characteristics and relationships between items and users. For example, an item embedding might encode information about its genre, director, and actors. Similarly, a user embedding might represent their preferences and behavior. These embedding can be learned using techniques like word2vec, GloVe, or more advanced models like Transformers. Word2vec Word2Vec is a popular algorithm used in natural language processing (NLP) to generate word embedding, which are vector representations of words in a high-dimensional space. The word embedding produced by Word2Vec capture semantic and syntactic relationships between words based on their context in a large corpus of text. The algorithm was introduced by researchers Mikolov T. at Google in 2013. Word2Vec is a shallow neural network model that learns word embedding by training on a large amount of text data. It makes use of a technique called "distributed representations," where words with similar meanings or that often appear together in context are represented by vectors that are close to each other in the vector space. There are two primary architectures in Word2Vec: Continuous Bag-of-Words (CBOW) and Skip-gram.

There is the CBOW model. The CBOW model aims to predict a target word based on its surrounding context words. It takes a sequence of context words as input and predicts the target word in the middle. The model learns to associate the context words with the target word by adjusting the weights of the neural network during training. There is the skip-gram model, on the other hand, takes a target word as input and predicts the surrounding context words. It tries to maximize the probability of the context words given the target word. The skip-gram model is generally slower to train but often produces better word embedding, especially for infrequent words.

Both CBOW and skip-gram models learn word embedding by optimizing the neural network using techniques such as stochastic gradient descent. The resulting word embedding can be used to measure the similarity between words, perform analogical reasoning tasks, and enhance various NLP applications such as text classification, information retrieval, and machine translation. Word2Vec has been widely adopted due to its ability to capture semantic relation-ships between words and its efficiency in training large-scale word embedding. It has played a significant role in advancing the field of NLP and has paved the way for sub-sequent developments in word representation learning.

Innovation approaches and algorithms being used in state-of-the-art recommender systems for e-commerce also are in particular graph-based models – graph-based approaches represent users, items, and their relationships as a graph structure. Graph Convolutional Networks (GCNs) and Graph Attention Networks (GATs) are used to capture the interdependencies between users and items, enabling more accurate recommendations; session-based recommendations which focus on capturing short-term user preferences based on their current session activity. Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks, and Transformer-based models are used to model sequential behavior and generate session-based recommendations, and knowledge graphs represent items, users, and their attributes in a structured form. By incorporating knowledge graphs, recommender systems can leverage semantic relationships between items and users to provide more contextually relevant recommendations. It's important to note that the field of recommender systems is continuously evolving, and researchers are actively working on developing new algorithms and techniques to enhance recommendation quality and address various challenges.

3. Results

The Figure 2 represents the architecture of a system for an e-commerce platform, including various components and their interactions. The system includes a “Customer” entity, an “API” package with interfaces such as “OrderServiceAPI”, “ProductServiceAPI”, and “CartServiceAPI”, and a “Services” package with components like “OrderServiceImpl”, “ProductServiceImpl”, and “CartServiceImpl”. Additionally, there are the “Databases” packages with databases such as “OrderDatabase”, “ProductDatabase”, and “CartDatabase”, and the “Message queues” package with queues named “OrderQueue” and “CartQueue”.

Furthermore, the diagram showcases the “Recommender system” package consisting of the following components: “RecommenderSystemAPI”: An interface facilitating interaction with the recommendation system. It provides access to the functionality of the recommendation system for communication with other components and external applications; “DataScienceService” - a service responsible for data processing and scientific computations within the recommendation system. It utilizes data from databases to analyze user preferences and offer personalized recommendations; “Chatbot” - an interface for user interaction. Users can ask questions, and the chatbot uses the “Knowledge_Base” to provide information and solutions. The “Knowledge_Base” contains instructions, solutions, and other useful data that assist the chatbot in answering user questions and providing recommendations; “Statistics_Records” - records statistical information on user requests. It logs queries that the chatbot couldn't answer, enabling analysis of these situations and improvement of the knowledge base.

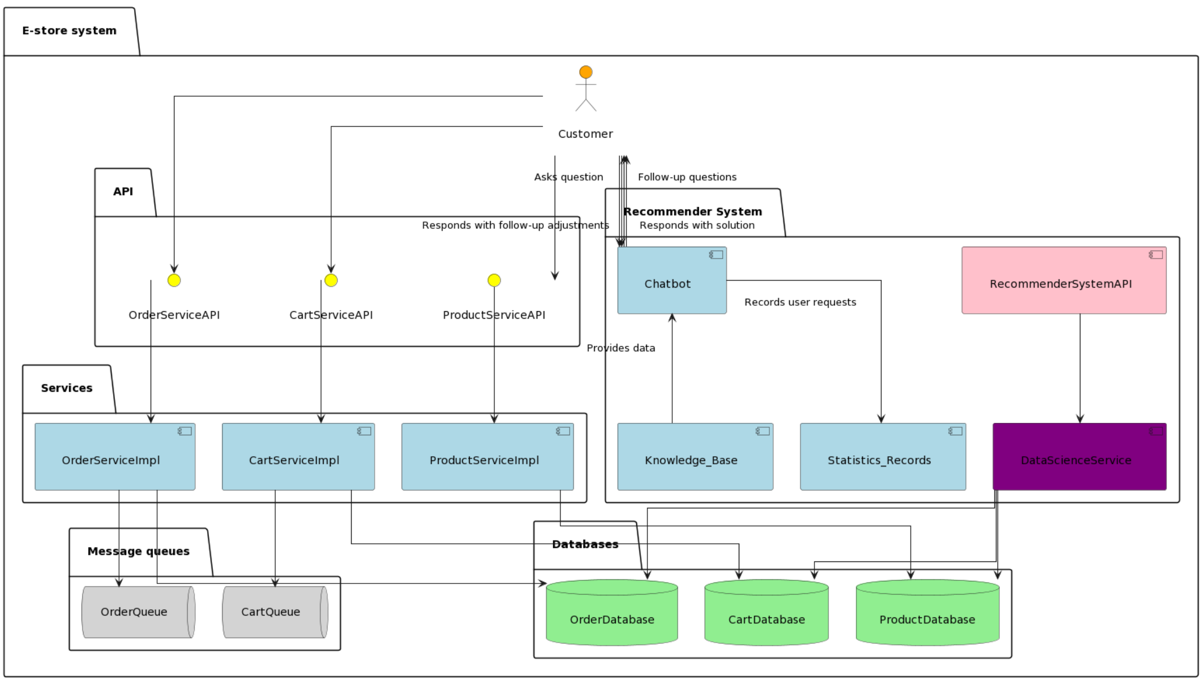

Figure 2: E-store architecture with recommender system

The “Chatbot” component interacts as follows:

- The user asks the AI a question;
- The AI utilizes the knowledge base, which contains instructions on how to solve the issue;
- The AI responds to the customer, and if additional questions arise, it processes them as well;
- The AI records statistical information on user requests, primarily focusing on questions it couldn't answer;

The “Recommender system” package brings together components related to the recommendation system, data processing, user interaction, and statistical analysis. It enables the provision of personalized recommendations and system enhancement based on user interaction and statistics.

4. Conclusions

In light of the transformation into a digital society, the development of the field of electronic economy, and in particular, electronic business and electronic commerce, is receiving a new impetus. Therefore, consumer behavior models and recommender systems in e-commerce are of particular importance. In the field of recommender systems for e-commerce, several future trends and directions are emerging. These trends are as follows: personalization and contextualization, explainability and transparency, usage of hybrid approaches, context-aware recommendations, group and social recommendations, reinforcement learning, privacy and trust, multimodal recommendations, long-tail recommendations, online learning and real-time recommendations, etc.

The focus is shifting towards highly personalized recommendations that consider individual preferences, behaviors, and context. Advanced techniques such as deep learning, natural language processing, and reinforcement learning are being employed to capture nuanced user preferences and deliver tailored recommendations. There is a growing demand for explainable recommender systems. Users want to understand why certain recommendations are made, particularly in the case of complex algorithms like deep neural networks. Techniques like attention mechanisms, rule-based explanations, and interpretable models are being explored to provide transparent recommendations.

Combining multiple recommendation techniques is gaining traction. Hybrid recommender systems integrate collaborative filtering, content-based filtering, and knowledge-based approaches to leverage the strengths of each method. This helps overcome limitations and provides more accurate and diverse recommendations. Incorporating contextual information such as time, location, weather, and social context can enhance the quality of recommendations. Context-aware recommender systems consider temporal dynamics, user context, and situational factors to deliver more relevant and timely suggestions. Recommending items to groups or communities rather than individuals is an evolving area. Social recommender systems leverage social network information, user interactions, and group dynamics to generate recommendations that align with collective interests and preferences.

Reinforcement learning techniques are being explored to optimize recommender systems. By using feedback loops, recommender systems can actively learn and adapt to user feedback, continuously improving the quality of recommendations over time. With increasing concerns about data privacy, there is a focus on developing recommender systems that respect user privacy. Techniques like federated learning, secure multi-party computation, and differential privacy are being researched to provide privacy-preserving recommendations while maintaining data security.

With the rise of multimedia content, recommender systems are being adapted to handle multiple modalities such as text, images, audio, and video. Techniques like multimodal fusion, deep learning, and cross-modal retrieval are used to provide recommendations based on diverse types of data. Traditional recommender systems tend to prioritize popular items, leading to limited exposure to niche or long-tail items. Addressing this, efforts are being made to pro-vide recommendations that promote serendipity, novelty, and diversity, ensuring users are exposed to a broader range of products.

Real-time recommendation systems that continuously adapt to evolving user preferences and dynamics are gaining importance. Online learning techniques enable systems to update recommendations in real-time, considering the most recent user interactions and changes in preferences. These trends represent ongoing research and development efforts in the field of recommender systems for e-commerce, aiming to provide more accurate, personalized, and context-aware recommendations while addressing user concerns regarding transparency, privacy, and diversity. By understanding the behavior and preferences of your customers, using recommender systems for e-commerce companies, you can create better products, provide personalized experiences, and develop effective marketing strategies that contribute to the development of e-commerce in general.

5. References

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