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Review Article

Transforming E-Commerce with Intelligent Recommendation Systems: A Review of Current Trends in Machine Learning and Deep Learning

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Abstract:

In the ever-changing realm of E-Commerce, it is essential for online businesses to comprehend and adjust to shifting consumer behaviour in order to achieve long-term success. In which, Intelligent Recommendation System (IRS) has gained familiarity by suggesting personalized information based on user preference and behaviours. Hence, the review paper primarily aims to analyse significance of the intelligent recommendation system to transform ecommerce field, specifically enrich the user personalisation and satisfaction, and enhance revenue in business. Accordingly, the proposed survey is discussed the traditional system and AI-powered personalization system in ecommerce. AI-powered recommendation system utilize sophisticated algorithms to analyse extensive data, allowing for the provision of highly customized and relevant content, product recommendation, and user satisfaction. Besides, it examines future trends in AI integration within e-commerce, particularly advancements in Natural Language Processing (NLP) and visual search technologies, which are poised to further enrich ecommerce. The paper concludes with a look toward future directions for the integration of AI technologies in e-commerce, anticipating advancements in NLP and visual search capabilities, which promise to further enhance the online shopping experience. Overall, the findings of the article underscores the transformative impact of IRS on the e-commerce sector, advocating for their continued development in response to evolving market demands.

1. Introduction

1.1 Background

In digital era, Electronic Commerce (E-Commerce) platform have revolutionized that anyone can purchase and promote their product with the help of internet, that allows consumers to shop at any time and from any location [1]. This level of convenience surpasses what physical stores can typically offer. As businesses greatly integrates e-commerce into their operations, they play an essential role in the economic growth of nations, particularly in developing countries [2]. E-commerce is reshaping how business is conducted and recognized as a vital component of the modern economy. It offers distinct benefits for consumers and businesses alike, driving economic growth and facilitating global commerce . Besides, it allows businesses to collect and analyze consumer data, helping them understand customer preferences and improve their offerings [3]. With technological advancements and changing consumer preferences, the e-commerce landscape is poised for significant transformations. Digital platforms like Walmart, Amazon, Alibab, Flipkart, and Shopsy offers a vast range of products, which can overwhelm customers and hinder their purchasing decisions [4]. This challenge underscores the necessity for effective Recommendation Systems (RSs) that can guide users toward suitable products, ultimately enhancing sales for businesses [5].

In present situation, RSs have become a vital tools for online platforms, assisting users in finding the items they desire among a wide array of available options. Recommender systems have been featured as personalized shopping assistants in large-scale e-commerce sites which can increase sales and loyalty and reduce customer churn [6]. By enhancing user experience and driving engagement, they contribute to increased sales for businesses. Common recommendations methods include collaborative filtering, which analyzes user preferences, content-based filtering that relies on item attributes, and hybrid approaches that combine these techniques for improved recommendations [7]. Traditional e-commerce recommendation system faces the challenges like scalability issues, declineing recommendation validity over time and its efficiency is relay on quality and quantity of the available data [8].

Conversely, to overcome these challeges the recommender system leverage artificial intelligence (AI) techniques, including Machine Learning [8], and Deep Learning (DL), to analyse vast amounts of data and enhance personalization[8, 9]. This not only boosts sales but also enhances customer satisfaction and increases conversion rates. The ML models have an ability to learn automatically and recognise the patterns, hence many researchers explored this approach to develop RS [10]. Likely, DL techniques utilizing artificial neural networks with multiple hidden layers have demonstrated remarkable effectiveness in accurately predicting outcomes for big data applications, especially in the context of RSs [11]. AI in e-commerce can be described as the application of artificial intelligence methods, systems, tools, or algorithms to facilitate activities associated with purchasing and selling goods or services online [12]. Hence, these systems improve operational efficiency by automating recommendations and allowing businesses to manage large volumes of data effectively.

The comprehensive review article provides the deep analysis on RSs that developed by ML and DL techniques and combined AI approach to enhance the e-commerce market. The results of this study suggest that the application of AI in e-commerce primarily focuses on RSs. Notable, research themes in this area include sentiment analysis, optimization, trust, and personalization. We conducted an extensive investigation using Google Scholar. Moreover, it provides the overview of the central themes and primary challenges investigated in recent studies at the intersection of ML, DL, RS and e-commerce.

1.2 Objectives of the review

The following key points are the primary goal of the present review article,

- To perform a review on both ML and DL based recommendation system and highlighting the findings from articles published in the past five years.
- To explore how ML and DL technologies improve the personalization of RS based on user behavior, preferences and suggesting complementary products.
- To analyse and highlight emerging trends in Intelligent Recommendation System (IRS) as well as the challenges faced in their implementation.

The review paper organised as follows, Section 2 that deliberates existing studies that incorporated ML and DL techniques in their studies. Following that, section 3 ellaborately discuss on utilization of AI technology in e-commerce recommendation models. After that, Section 4 describes contribution of the recommendation model. In following, section 5 illustrates practical implications, section 6 demonstrates Future Directions and Limitations in section 7, at last section 8 with Conclusion of the present study.

2. Methodology

2.1 Research Question

The following expresses the research questions of the present study:

1. What challenges do e-commerce platform face while implementing IRS and they can be addressed?
2. How can the integration of DL techniques improve the accuracy and relevance of recommendations compared to traditional ML approaches?
3. What role does consumer self-concept play in enhancing the effectiveness of personalized recommendations in e-commerce?
4. How do different recommendation algorithms impact user engagement and sales performance in e-commerce platforms?

2.2 Sources selection

This review paper focuses particularly on Intelligent Recommendation System (IRS) to transform the field of e-commerce by analysing the past five years between 2021-2025 published research studies, which serves as a key exclusion criterion. In this study, we utilized a thorough search methodology that included multiple online databases and a careful examination of the selected literature. Additionally, the language of publication was considered an important exclusion factor; non-English publications, not specific on e-commerce and study with insufficient experiments were filtered out by configuring the search engine to exclude them prior to retrieving results from digital libraries. Besides, we performed a manual evaluation by reviewing the titles and abstracts conclusion, and keywords of the papers. We then selected the relevant studies while excluding those considered irrelevant. The process of manually reviewing and assessing the relevance of each publication is referred to as analysis.

Table 1. *Summary of the search results based on the database.*

Database Name	Number of Study
IEEE	3
MDPI	5
Springer	8
Taylor & Francis	3
Science direct	7
Willey	1
Research Gate	7
Others	30
Total	**63**

From the table 1 the study prioritized sources like IEEE, MDPI, Springer and Science direct for their reputation for rigorous peer review and high-quality publications in technology and engineering. Selecting these sources ensures the credibility and impact of the research, aligning with the study's focus on deep learning and recommendation systems. This choice enhances visibility and contributes to advancements in the field by building on reliable and cutting-edge research.

Figure 1. *The Publication details*

The figure 1 illustrates that the proposed review study has utilized mostly standard publications, to investigate on the recommendation models importance in ecommerce. The study is carried out with latest last five year research paper that can be described in table 2 as follows,

Table 2. *Year wise exiting studies details*

Year	References
2021	3
2022	8
2023	25
2024	22
2025	5

The table 2 describes the total references used in this review article and provides the year wise split. Besides, it defines that we utilized more recent studies in this survey than old works. It depicts the number of published references taken to review on the RS. It is used 3 references in 2021, and 8 research paper in 2022 is considered, while 24 papers taken from year 2023, indicating a peak in interest. Likewise, the study investigated on 20 papers in 2024 and most recent 2025 year 5 papers are taken. The figure 2 depict the graphical illustration of the table 2 that shows the reference details based on year.

Figure 2. *Demonstration Year-Wise Publication.*

2.3 Literature search

This section presents an analysis of various existing studies on RS by using ML and DL models to transform ecommerce business.

Machine Learning Approaches

Machine learning approaches [13] such as supervised approach, unsupervised, semi-supervised learning and reinforcement learning are established to significantly transforming the e-commerce landscape by implementing better recommendation model that enhancing the customer experiences, optimizing operations, and driving revenue growth.

Consequently, Loukili et al, [14] the study aimed to enhance e-commerce experiences through personalized recommendations, recognizing the critical role of recommender systems in driving customer engagement and sales. It has involved developing an algorithm that utilized association rules via the FrequentPattern-Growth algorithm to suggest products based on customer behavior. The findings have revealed that the algorithm significantly boosts purchase probabilities for recommended items, underscoring the critical role of personalized recommendations in enhancing customer engagement, and deals for e-commerce platforms. Another approach [15] has combined fuzzy logic with Black Hole-based Grey Wolf

Optimization (BH-GWO) optimisation toimprove sentiment analysis and enhanced RS. It has customer reviews and feedback, optimization technique enhances the feature extraction process by efficiently tuning parameters, leading to improved classification accuracy system measured against benchmark datasets. Hence, his innovative approach has provided a framework for developing personalized RS that adapt to user preferences and market trends.

Accordingly, the study [16] had introduced ML-Recommend, a recommendation model that integrated with Microsoft's ML.NET platform, designed to streamline the entire recommendation modeling process. It employed utilizing matrix factorization and logistic regression to analyse product ratings and customer feedback. The model was validated through experiments on the UEL Store e-commerce site and the UCI sentiment-labelled dataset, achieving effective product recommendations based on user-configured expected scores. The performance of the model has shown that ML-Recommend model could be prominent for effective ecommerce business. Moreover, Gulzar et al, [17] has invented ML based model to overcome the cold-start and data sparsity in e-commerce RS by employing Ordered Clustering-based Algorithm (OCA). It has conducted to enhance recommendation accuracy by clustering users based on preference similarities, utilizing collaborative filtering. Finally, the results have demonstrated that OCA significantly improved recommendation model performance and revealed effectiveness in overcoming common RS issues. Similarly, Patro at al., [18] has established to overcome cold-start and data sparsity by implementing four phase approach, grouping similar users using Ant-Lion based k-means clustering, applying Higher-Order Singular Value Decomposition (HOSVD) for dimensionality reduction, and employing Adaptive Neuro-Fuzzy Inference System (ANFIS) for output prediction. It has obtained moderated outcome and demonstrating its effectiveness in enhancing recommendations to increase targeted customer in ecommerce. Similarly, in study [19] has addressed cold start and data sparsity problems in RSs by proposing a three-stage approach that combined clustering, Association Rule Mining (ARM), and personalized suggestions. Results have revealed significant performance improvements over other techniques, highlighting the method's effectiveness and scalability for large-scale applications. Likewise, Rajeshirke SS. [20] has implemented a personalized recommender system using advanced matrix factorization techniques to addresses the issue of enhancing user experience through recommendations in online platforms. It has leveraged user behaviour data to generate tailored recommendations, achieved high precision 0.92 and a balanced F1-score 0.68. It has emphasized the potential of matrix factorization in recommender to improve scalability with diverse user preferences.

Deep Learning Approaches

DL models can be a subset of ML and learn the complex pattern by utilizing the neural network layers with interconnected nodes to enable extraction of releavant feature from input data. In RS, the DL approaches leverage advanced neural network architectures to enhance the accuracy and relevance of item suggestions [21].

Likewise, Latha, Y.M. and Rao, B.S., [22] dveloped a DL model to over the limitations in the user’s browsing history and transaction history. Hence, has invented the product review based recommendaton system by employing DL framework. It has collected the data from amazon product review dataset, TF-IDF applied for feature extraction and Convolutional Neural Network (CNN) model with skip-gram in the word-embedding layer for predicting the relevant product range by means of user preference. Thus, the model has attained a mean recall of 94.80%, the precision of 93.64%, and accuracy of 96.92% on the amazon product reviews database. Similarly, Salampasis et al., [23] has invented the Session-based Recommendation System (SBSR) in e-commerce applications particularly in scenarios where user profiles and purchase data are unavailable. It has employed a statistical co-occurrence techniques, embeddings, and DL model such as Long-Short Term Memory (LSTM) and evaluated SBRS task and tested with various dataset. Those models have focused on tasks such as predicting the next item, next basket, and purchase intent. The comparative analysis has emphasized that LSTM model outperformed in all SBRS task and proven the significance of the SBRS recommending model in e-shop platform. Another [24] work tackled the inefficiency in utilizing sequential data for e-commerce recommendations, focusing on how early user actions influence current decisions. It has proposed the DELIGHT Sequential Recommender System (DSRS), which segments user behavior into long- and short-term preferences for improved predictions. The outcomes have shown that DSRS outperforms existing models in capturing long-term dependencies, enhancing the overall user experience. Another work [25] has addressed the issue of information overload in RSs, particularly in e-commerce, where users often receive excessive and irrelevant suggestions. It has implemented IRS using ensemble learning to enhance the precision and recall of recommendations by considering purchase history and additionaly browsing behavior, wish lists, and user reviews. It has involved analyzing various user activities and implementing ensemble learning techniques to filter out duplicates and irrelevant suggestions. The results have indicated a significant improvement in the system's performance, user satisfaction and decision-making. This approach has demonstrated that providing more relevant recommendations, thereby enhancing the overall user experience in e-commerce environments. As suggested by Karabila et al., [26] has focused to enhance the ecoomerce RS by integrating Sentiment Analysis (SA) with collaborative filtering techniques. It has combinee ensemble learning methods with sentiment analysis to refine RS, employed Bidirectional Long Short-Term Memory (Bi-LSTM) for sentiment modeling and integrating this with collaborative filtering. This model has achieved an impressive accuracy score of 93%, outperformed than other existing models. It has highlighted that leveraging sentiment analysis alongside traditional collaborative filtering techniques could lead to more effective and individualized RS in e-commerce environment. As stated by Shokrzadeh Z et al., [27] has invented knowledge graph- based recommendation system to address the obstacles like ambiguity and redundancy. It has learned dimensional vector reprresentation following hat collaborative filtering has been applied to leverage the feature extraction. The experimental outcomes has obtained that 3.87%, 2.42%, and 6.05% those could be average of recall, precision, and F1-score respectively.

AI-driven Approaches

Xu et al., [28] has investigated the effectiveness of personalized RSs in e-commerce, contrasting them with traditional classification methods. it hasinclude a comparative analysis of these systems, focusing on challenges like data privacy and algorithmic bias, while proposing a solution utilizing the BERT model and nearest neighbor algorithm tailored for eBay. The findings highlight that the model enhances user engagement and satisfaction through personalized recommendations, addressing challenges for improved operational effectiveness in e-commerce platforms. Smilary, another study [29] has developed to overcome the the challenges in e-commerce due to the vast data volume and low value density by implementing ML based approach to analyze user habits and enhance platform performance. Using user data it has generated a matrix calculation model to evaluate user ratings and establish a time interval calculation matrix, ultimately aiming to create a comprehensive user information system. The findings suggested that the model effectively improved user insights in e-commerce domain. According to Shirkhani et al., [30] has implemented a AI model to tackle the challenges in RSs in an increasingly diverse and fast-paced industry like ecommerce, highlighting the need for compatibility over mere similarity in product recommendations. It has established AI techniques in recommender systems, particularly focusing on image-based systems and has improved recommendation quality. The results have indicated that AI-driven systems significantly outperformed than traditional methods, and emphasized the importance of understanding fashion-specific characteristics to optimize recommender systems in this unique domain. Accordingly, the study implemented to address the challenge of slanderous user detection in RSs, where users intentionally submit fake reviews and low ratings to manipulate the system. Thus, it has developed a framework called Slanderous user Detection Recommender System (SDRS), employing a Hierarchical Dual-Attention Recurrent Neural Network (HDAN) with a modified GRU to analyze review sentiments and detect discrepancies between ratings and reviews. The results from experiments on datasets like Amazon and Yelp have demonstrated that SDRS model effectively identified slanderous users and enhanced recommendation accuracy. Finally, it emphasized that integrating slanderous user detection can significantly improve the performance of existing RSs by filtering out deceptive information [31]. Likewise, in study [32] a Quantum-Enhanced Recommendation System (QERS) has proposed to addresses the challenges of computational complexity and scalability in traditional RSs, especially for large-scale e-commerce platforms. It has developed a hybrid quantum-classical architecture utilizing quantum principal component analysis (qPCR) and quantum similarity computation, implemented on simulated quantum devices across various datasets. The findings of the study has indicated 87.3% reduction in execution time and a 15.8% increase in precision compared to classical methods. Hence, it has showcased the significance to enhance personalized recommendations in e-commerce to increase business.

3. Utilization of AI technology in E-commerce Recommendation Models

3.1 Types of Recommendation model in E-commerce

Generally, RS is optimized to enhance the user experience by providing personalized suggestions. It can be done by leveraging various techniques in

AI algorithms include collaborative filtering, Content-based filtering and integrated approaches to improve accuracy and diversity in recommendations, adapting to user behaviour over time. The figure 3 illustrates the overall types in recommendation models,

Collaborative Filtering - It uses past user behaviour data to recognize preference trends within a community. This technique can be implemented in memory or offline using linear techniques like matrix factorization (MF) and graph-based approaches, as well as nonlinear methods like deep neural networks (DNN), and others.

Content-based Filtering – This systems incorporate both contextual information about the user and historical data about the products.

Integrated ML and DL Approach- AI-based methods can leverages both ML and DL techniques, resulting in more intelligent recommendation systems. For instance, smart systems utilizing AI have the ability to analyze vast amounts of data in order to offer precise and tailored suggestions dependent on user actions, likes, and choices.

Traditional algorithm such us collaborative filtering and content based filtering is faced the issues such as cold start problem and data sparsity. Therefore, the study [33] has implemented to address the issues in the traditional collaborative filtering method like lacked to consider social association among users. The primary focus could be integrate collaborative filtering with social networks to enhance the precision and relevance of the recommendations by computing user similarity based on both ratings and social connections. It has utilized modified user-based collaborative filtering algorithm that used a weighted combination of ratings and social connections, with weights optimized through a learning process, and is evaluated using a dataset of movie ratings and social connections. The outcome has revealed that the model significantly outperformed than traditional model in terms of recommendation accuracy and diversity also suggested its potential applications in various domains such as e-commerce and entertainment. Accordingly, in the study [34] recommendation model has developed to analyse both ratings and reviews based on the ensemble DL approach. It has analysed both ratings and reviews to enhance the recommendation process by conducting sentiment analysis on reviews, which yields numerical values for polarity and subjectivity.) This method has involved scaling inputs to ensure compatibility, employing a Deep Neural Network (DNN) with multiple hidden layers for effective learning, and assessing various architectural configurations based on precision, loss, and execution time. The results have indicated that while the model shown improvements that needed in interpretability to enhance credibility. Another study [35], has implemented to overcome the issue in collaborative filtering by integrating collaborative filtering and content based filtering to offer product suggestions for new as well as old users. It has tailored recommendations to meet the demands of current users based on their historical purchasing patterns, feedback, and actions. It has examined content similarity and determined items related hence generated recommendation based on it. Besides, new customer revived notification regarding the new items. The model performance evaluated through Walmart product rating dataset and the model highlighted the importance of advanced algorithms in RS to transform ecommerce, enrich user satisfaction and boost sales.

Another study [36] has established to boost the Content-based recommendation with Open- and

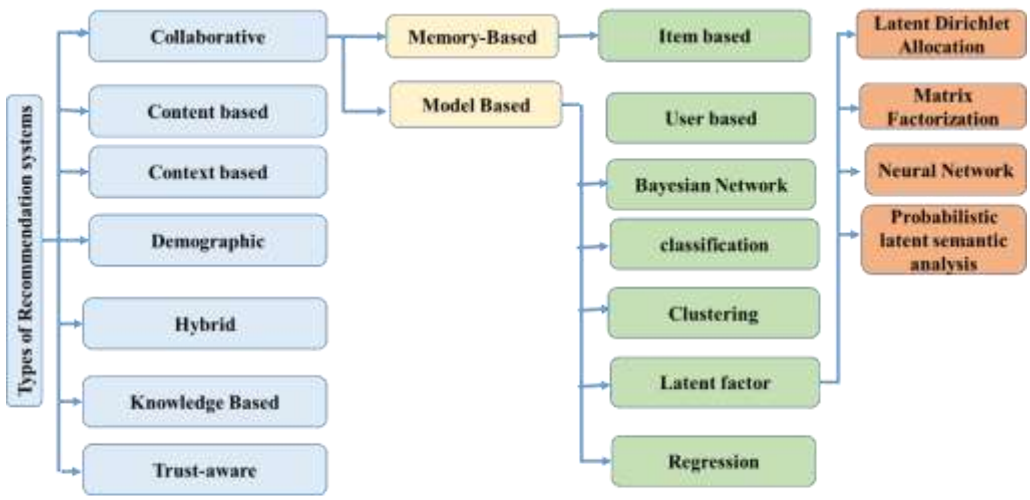

Figure 3. *The types of recommendation models*

Closed-source Large Language Models (LLMs). In which open-source LLMs serve as content encoders to improve item representation, while closed-source LLMs employed prompting techniques to enrich training data. The results have demonstrated a significant relative improvement of up to 19.32% over existing state-of-the-art models, highlighting the synergistic benefits of combining these approaches. In study a session based recommendation has developed by gradient descent temporal convolution neural network (GDTCNN) specifically for e-commerce applications, leveraging DL to analyze non-linear data and improve recommendation accuracy. The main contribution of this approach include non-linear distortion handling, knowledge discovery, and adaptability. The primary data transformation utilized the Box-Cox transformation to convert invalid data into valid information and shown the significant improvement in accuracy and model performance. Similarly, in study [37] introduced a recommendation system that boosts online shopping by suggesting relevant items using both visual (ResNet-50) and textual analysis of product data by term frequency-inverse document frequency (TF-IDF). By combining these methods, the system has achieved 94.72% accuracy in subcategory classification, a 4% increase over CNN alone. This confirms the system's effectiveness in providing relevant product recommendations to online shoppers.

Similarly, the study [38] established to develop a deep neural collaborative filtering RS to enhance product recommendations based on user preferences. It has deployed advanced ML techniques to analyze user-item interactions and optimize recommendation accuracy. The model has achieved a precision of 0.85, a recall score of 0.78, and a click-through rate of 0.12, demonstrating its effectiveness in engaging users with relevant suggestions. Finally. It has highlighted the critical role of sophisticated RS in improving the shopping experience and driving sales growth in a competitive digital marketplace. Likewise, this study [39] has addressed the issue of preference noise in DL based RSs, which often rely on implicit feedback and neglect the impact of unreliable explicit ratings. To counter this, developed a deep neural recommendation framework that incorporated rating reliability derived from ratings themselves. The framework has employed a noise detection method based on intuitionistic fuzzy sets to identify and label incorrect ratings, creating a binary rating reliability matrix. Experimental results on widely used datasets demonstrated an average improvement of 9.4% in Recall and 8.0% in NDCG compared to existing methods, highlighting the effectiveness of integrating rating reliability to enhance recommendation performance.

Another study [40] has combined collaborative filtering techniques with advanced neural network algorithms to enhance AI-powered recommendation engines. It has analysed user and item interactions through collaborative filtering, while DL model has utilized to capture complex relationships and temporal dynamics in user behavior. Model efficiency examined on diverse dataset and highlighted the potential improvements in recommendation accuracy, diversity, and user satisfaction compared to conventional approaches. Likewise, the prior study [41] has introduced BERTFusionDNN framework that combined BERT and a DNN to extract textual and numerical features. The model efficiency has been tested on a Women Clothing E-Commerce dataset and compared it to other methods. Our approach effectively gathers insights from customer reviews, improving e-commerce RSs by overcoming challenges with understanding both text and numbers. In study [42], a transformer pre-raining model has used in ecommerce RS. It has analysed scenarios such as product description generation, sentiment analysis, personalized recommendation systems, and customer service automation. The findings has emphasized the importance of pre-training model in understanding user intentions and improving recommendation quality.

3.2 Key Components in AI-Driven Recommendations System

AI based RS examine large dataset to uncover patterns and generate accurate predictions. ML and DL approaches could be deployed to enhance personalized suggestion to user hence not only enhance the sales in ecommerce as well as improve the user satisfaction. Particularly, in ecommerce domain AI technology has provided better relationship among customers and retailers [43]. AI model gathers both explicit data and implicit data to understand user preferences that details gathered from user profiles, interconnection logs and feedback or reviews given by the user. To build sophisticated recommendation system it is essential to integrate key concepts from consumer behavior theories with AI techniques [44]. The following figure 4 demonstrates the key elements interconnected in IRS.

IRS enhance online business and shopping experience of the customer by providing comprehensive suggestion on their interested items[45]. Accordingly, the existing work has focused to develop RS based on collaborative

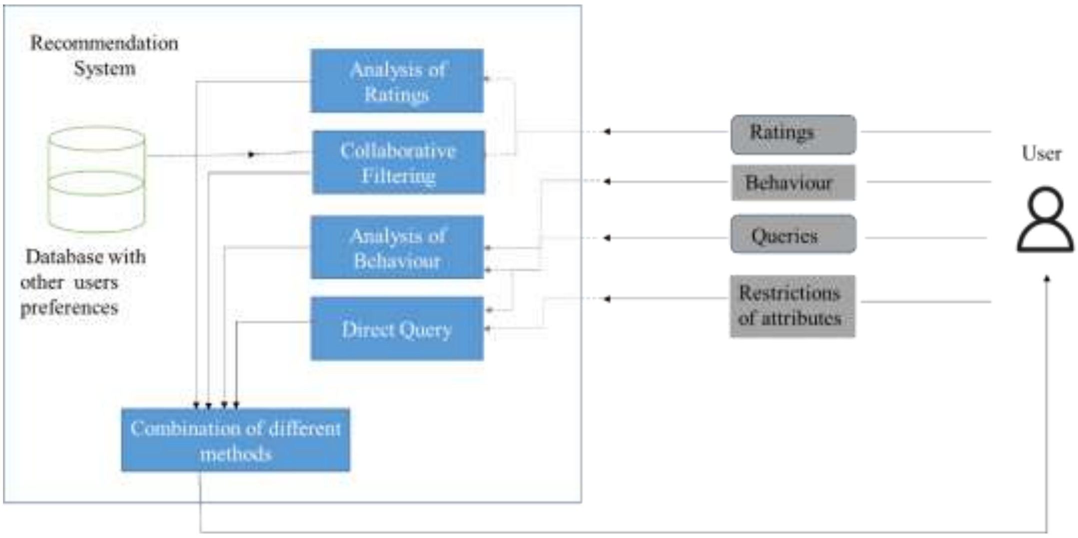

Figure 4. *Key Elements Interconnected in Recommendation System*

filtering then improved as an IRS system with ML methods by overcoming the labelling classification on it. The findings has proven that this approach significantly enhance the performance of the traditional recommendation model [46]. Another study has developed a personalized next basket recommendations in grocery shopping by using both ML and DL approaches. The main goal of the model could be to assist Canadian customers in generating personalized, intelligent weekly grocery lists that take into account their unique purchase histories, local store weekly specials, and information on product costs and availability. It has performed clustering analysis to split requirements then ML and DL concept has been applied. DL model has generated based on Gated Recurrent Unit (GRU) and Recurrent Neural Network (RNN) architecture and adopted multi store details because the user could purchase item from where ever available. The findings has shown that developed DL models have achieved average F1-score of 0.559 which could be higher than the F1 score obtained by the traditional ML model.

In ecommerce platform a text based recommendation possess the limitation to determine the similarity in the product. Thus, in study image based search for recommendation could be considered based on ML method. Principal Component Analysis (PCA) applied for dimensionality reduction in the image and Singular Value Decomposition (SVD) has employed to convert the extracted features into a lower-dimensional space. Then, it has utilized K-Means++ clustering approach to group the similarity of the item. The model efficiency has been compared with other unsupervised learning models and the dataset has contain 40,000 fashion item images. The model has attained the a Silhouette Coefficient of 0.141, a Calinski-Harabasz index score of 669.40, and a Davies Bouldin index score of 1.854 and proven its superiority of the image based recommendation models [47].

3.3 AI-Powered Enhancements in Recommendation system

AI algorithms enhanced personalization for product recommendations by tailoring suggestions based on individual customer preferences and behaviours. Additionally, the personalized RS can create customized coupons and promotional activities for users based on their purchase history, preferences, and requirements. By delivering coupons and promotional content that align with users' interests and needs, e-commerce platforms can enhance user engagement and loyalty, while also encouraging more purchases [48]. Accordingly, the study investigated on the three personalized recommendation model to analyse the importance of the personalization, the models namely Non-personalized, Partially personalized, and Most personalized. The findings from the theoretical analysis the result concludes that most personalized recommendation enlarge the ecommerce landscape. Hence, personalized recommendation become highly essential component in the ecommerce [49]. To create effective personalized recommendations, e- business could analyse various aspects of user behaviour, including

Clickstream Analysis: This involves tracking the sequence of pages a user visits to understand their interests and navigation patterns.

Purchase History Analysis: In this examining the past purchases based on that identify preferences of the customer and suggest related products.

Search Query Analysis: It analyse according with the user's search regarding required product details then understanding their interests, enabling targeted recommendation [50].

Implementing AI-enhanced personalization in RSs offers several significant benefits. It can improve customer satisfaction, ensures long-term loyalty and increased sales and revenue. Companies like Amazon, Walmart, Shopsy, Flipkart and Alibaba utilizing advanced AI for personalization also enhanced brand perception, positioning themselves as innovative leaders in their markets. Furthermore, streamlined inventory management is facilitated by a better understanding of customer preferences, optimizing stock levels and reducing waste in ecommerce [51].

Consequently, the study [52] aimed to explore the use of ML algorithms to predict customer behaviour in e-commerce platforms. It employed supervised and unsupervised learning techniques, including decision trees, neural networks, and clustering, with performance assessed using precision, recall, and F1-score metrics. The results have indicated that these models effectively enhanced predictive accuracy, demonstrating the potential of ML to optimize marketing strategies and improve customer retention. Similarly, the suggested study [53] has focused on integration of AI and ML within ecommerce to enhance customer enhancement through personalized experiences. It has explored AI-driven personalization strategies could improve key customer engagement metrics such as click-through rates and customer satisfaction. It has analysed various ML methods, clustering algorithms, and predictive analysis along with case studies and empirical analysis. The findings have highlighted that integrating AI-driven personalization in ecommerce platforms like Salesforce can significantly boost customer engagement and strengthen relationships, driving business growth and competitiveness. Similarly, the study [54] developed to tackle the issue like cold start problem with the limitations of the Deep Reinforcement Learning (DRL) methods that primarily consider single-hop social relationships, resulting in sub-optimal recommendations. Thus, it has developed Social Graph Neural Network-based Interactive Recommendation (SGNR) scheme that enhances DRL by incorporating multiple-hop social relationships to improve recommendation quality. In this methodology, a graph neural network has been utilized to extract these relationships from social networks, thereby leveraging richer user interactions for personalized recommendations. The model efficiency evaluated through two real-world datasets and findings have demonstrated that SGNR significantly outperformed than DRL-based methods. Besides, SGNR effectively mitigates cold-start issues and enhanced recommendation accuracy by fully utilizing multi-hop social connections.

3.4 Real world Applications with AI- based Recommendation systems

In e-commerce, AI-driven RSs are information filtering tools that offer consumers tailored suggestions based on their past experiences with the platform or other users who are similar to them, as well as their interests and habits. By assisting users in finding pertinent goods or services that they might find interesting, these technologies enhance the shopping experience for customers and boost engagement and revenue for online retailers. This facility can increase revenue and improve client engagement. In order to provide tailored product recommendations, these systems use sophisticated algorithms to evaluate enormous volumes of consumer data, such as browsing history, buying patterns, and preferences.

The primary benefit of e-commerce RS, which employs various methods like rating, ranking, or reviewing, its ability to find new products or the best products based on client personalization patterns. These suggestions can be developed using a variety of methods and strategies, especially with the use of intelligent agent technology [55]. In recent days, specifically AI algorithms were used to enhance recommender systems, this recommender algorithms were now a crucial component of practically all e-commerce platforms since it makes sense in development. AI is a combination of ML and DL techniques utilized by the developers to assist users predict their preferences and get related suggestions [56]. Companies like Walmart, Amazon, Alibaba and Netflix are prime examples of this tactic, as they significantly boost customer engagement and conversion rates by tailoring recommendations according to user preferences.[57]. E-commerce accounted for 16.2% of total retail sales in the US as of Q3 2024. According to the survey of Digital Commerce 360 reports a 7.5% year-over-year e-commerce sales growth in Q3, outpacing total retail sales growth. Experts predict sales will reach $1.26 trillion by the end of the year and $1.72 trillion by 2027.

Case study 1: Alibaba's Innovation with AI

Alibaba integrates AI to enhance efficiency, customer satisfaction, and business growth. They employ AI-powered chatbots such as Wanxiang, Alibee Shop, Alime, and AI bot to offer 24/7 customer support, answer queries, and mediate disputes. AI is also used in smart logistics, inventory management, and supply chain synchronization. Alibaba Cloud uses AI and ML to analyze user behavior and purchase history to deliver personalized recommendations.

Case study 2: Amazon e-commerce with AI technology
Like Alibaba, Amazon leverages AI across its e-commerce platform to enhance customer experience and streamline seller operations. AI algorithms provide personalized product recommendations based on user data and shopping habits. Amazon's team employed Graph Neural Networks (GNNs) [58] in order to provide recommender systems with additional context about the connections among products. This allows them to address the issue of uneven product recommendations. Recently, in Amazon AI-powered assistants like Project Amelia and Rufus offer support to sellers and expert shopping advice to customers. AI tools also automate product listing creation and generate brand imagery. The company optimizes warehouse operations, predicts demand, and employs "just walk out" technology in Amazon Go stores. AI is further utilized to improve search query understanding and address challenges in online fashion shopping [59].

Case Study 3: Walmart AI tools
Similarly, Walmart employs AI to personalize shopping through voice ordering and chatbots that handle customer inquiries efficiently. AI manages inventory, optimizes routes for deliveries, and powers the "Ask Sam" voice assistant for in-store navigation. GenAI platforms trained on Walmart data enhance customer support and automate tasks. These AI-driven initiatives aim to improve customer service, streamline operations, and optimize inventory management.

3.5 Challenges and Limitations in Recommendation system

Challenges and trends for ML and DL in e-commerce research, as follows:

- Imbalanced data poses a major challenge for both ML and DL based classification tasks in e-commerce. To solve this issue, various methods can be applied, including resampling techniques, weighted training, and transfer learning.
- Ensemble techniques such as bagging and boosting combine multiple models to improve overall performance and reduce overfitting. Hybrid models integrate different types of machine learning and deep learning algorithms, leveraging the strengths of each to improve the overall generalization ability.
- Multimodal learning poses significant challenges for machine learning and deep learning approaches in e-commerce. Despite these challenges, multimodal learning shows great potential for improving e-commerce applications.
- Model interpretability poses a major challenge for both machine learning and deep learning approaches in the e-commerce domain. It explore interpretability techniques such as feature visualization, attention mechanisms, and gradient-based methods to shed light on how machine learning and deep learning models work, thus increasing transparency and accountability of the decision-making process in e-commerce.
- Real-time inference capabilities are crucial for e-commerce platforms as they provide instant recommendations and predictions to users. Moreover, transfer learning has proven to be a valuable strategy to refine pre-trained models and improve their performance on specific e-commerce tasks, reducing the need for extensive data collection and training efforts. These survey-based trends highlight the growing importance of personalization and customer-centric strategies in the dynamic e-commerce environment.
- Chatbots and virtual assistants powered by machine learning and deep learning are indeed becoming a new trend in e-commerce. As e-commerce platforms strive to improve customer loyalty and streamline support processes, the adoption of machine learning and deep learning for chatbots and virtual assistants is expected to become prevalent in the e-commerce industry.

3.6 Ethical Considerations in AI-Powered Recommendation Systems

While involving AI technology in development of IRS to landscape the e commerce business need to consider ethics and issue related with it [60]. This article examines ethical issues related to AI-driven personalization, focusing on concerns about transparency and accountability, algorithmic bias, and the need to balance customization with user profile and privacy, creates impact on society. It emphasizes the significance of regulatory frameworks and industry standards to promote ethical AI practices in e-commerce.
Transparency and Accountability- Basically AI-powered recommendation models, particularly those employed DL methods, function as "black boxes," making their decision-making processes opaque. It is essential for users and sponsors to receive clear explanations of how suggestions are produced [61]. Accountability mechanisms must be established to manage any adverse effects resulting

from the use of recommender system. This includes implementing process that allow user to report problems and ensuring that these issues are tackled effectively.

Algorithmic Bias - Recommender systems can unintentionally reinforce or exacerbate existing biases found in the training data, resulting in unfair treatment of specific user groups and perpetuating stereotypes or discriminatory practices. Achieving equity in recommendations is a significant challenge, as it is essential to ensure that suggestions are fair and equitable for all user demographics. Therefore, methods for identifying and mitigating bias should be incorporated into the development process

User Profile and Privacy- While AI personalization enhances content and recommendation relevance by analyzing extensive datasets of user behavior and preferences, it also raises substantial privacy concerns as consumers become increasingly aware of how their personal information is collected, stored, and used by e-commerce platforms [62]. RSs typically require extensive data collection, raising significant privacy issues. Users may be unaware of how their data is collected, stored, and utilized, leading to potential misuse and erosion of trust [63].

Impact on Society- Recommender systems can generate filter bubbles by repeatedly showing users content that matches their current preferences and beliefs, which restricts their exposure to a variety of viewpoints and may contribute to societal polarization. Additionally, the pervasive use of these systems can shape cultural trends and social norms [64].

Dealing with these ethical dilemmas associated with RSs necessitates a thorough approach that involves developing robust technical solutions, adhering to regulatory frameworks, and instilling a sense of ethical responsibility among developers and stakeholders. This holistic strategy is essential to ensuring that these systems operate transparently and impartially while safeguarding user privacy and autonomy. Prioritizing ethical considerations enables us to harness the advantages of recommender systems such as enhanced user experience and personalized content while mitigating potential negative ramifications such as bias, unjust treatment, and a loss of trust. This proactive stance not only safeguards users but also fosters a more equitable digital environment that benefits all involved parties.

4. Theoretical Contribution

The incorporation of IRS in e-commerce has transformed the businesses engross with consumers. In this survey, theoretical contributions of recent studies that are focusing on ML and DL technologies in improving these systems. Moreover, the IRS uses algorithms to analyze consumer data, provide personalized product recommendations. Moreover, these structures mostly depend on two methods such as collaborative and content-based filtering, frequently joined with hybrid models to influence the robustness of approaches. The theoretical structures established in current studies contribute to insight these systems are enhanced for improved customer engagement with fulfilment.

The major contribution are expressed below and it is as follows,

In accordance with the hybrid models, the customer behavior analysis with recommendation algorithms in e-commerce that improves the personalization with significance of product recommendations. These hybrid models syndicates collaborative content-oriented filtering by radical ML methods to generate contextual suggestions personalized to features like regional inclinations with conditions. By using data mining approaches to expose arrangements for customer behaviour, and can adjust dynamically to modify in customer inclinations, providing restrictions such as cold-start difficulties and data insufficiency. Additionally, the outline of robust performance metrics permits for the computable valuation of recommendation efficiency, enabling uninterrupted optimization.

Correspondingly, the structure established insights of interrelationships between significant concepts like customer reliance, responsiveness, and approaches to RS, giving valued perceptions of advertising experts. Moreover, theoretic impact sets a basis for imminent exploration, highlighting the requirement of insights consumer behavior in the progress of operational RS approaches which improve engagement of the user and determine transactions in e-commerce settings. Through incorporating the concepts in real-time applications, vendors can modify the approaches to enhance consumer requirements and inclinations, finally refining the efficiency of RS in prompting purchasing results.

Current research shows that integrating psychological factors such as incorporation of self-perceived identity into recommendation algorithms can significantly improve their effectiveness. This approach seeks to address discrepancies in consumer behaviour by quantifying the psychological indications that influence decision-making. Incorporating these factors allows RS to be better tailored to users' identities and personal motivations, resulting in more relevant and compelling product suggestions. Likewise, theoretical frameworks for the evaluation of recommender systems emphasize the importance of performance metrics. Key metrics such as user satisfaction, conversion rates, and click-through rates are important for evaluating the effectiveness of different algorithms and models. Analysing these metrics allows companies to validate the impact of RS on the overall user experience and make informed improvements. These evaluations help ensure that recommendations are accurate and positively impact user engagement and purchasing behaviour.

Exploration is how complex algorithms such as Neural Network (NN) can be integrated with traditional collaborative filtering techniques to improve the predictive accuracy of RS. This hybrid approach aims to leverage the strengths of both methods to provide more accurate recommendations while maintaining the explain ability that is important to substitute user reliance. By combining the data-driven insights of NN with the user-based preferences of collaborative filtering, these systems are able to provide more relevant suggestions while being more transparent about the reasons for those suggestions. Knowledge-based recommendation systems (KB-RS) solve the cold start problem by leveraging explicit knowledge of user preferences and item properties. This approach enables these systems to provide relevant recommendations even for new users and items that lack rich historical data. By focusing on predefined user requirements and detailed item attributes, KB-RS can provide customized suggestions based on specific criteria rather than relying solely on past interactions. This feature is particularly useful in scenarios where historical data is scarce, ensuring that users receive meaningful recommendations right from the start.

5. Practical Implications

Analyzing user behavior and dynamically adapting content is essential to enhance personalized shopping experiences through IRS. ML algorithms evaluate user data, such as clicks, browses, and purchases, to determine preferences. Moreover, dynamic content customization personalizes experiences in real time and allows e-commerce platforms to refine these systems through A/B testing to determine the most effective strategies to increase user engagement. Recommendation algorithms can suggest products at key moments, such as during the checkout process and in emails in case of abandoned purchases, thus increasing purchase completion rates. Similarly, improving user retention in e-commerce hinges on fostering customer loyalty and engagement through IRS. These systems strengthen relationships by remembering user preferences and personalizing communications, making customers feel valued. Integrating recommendations into loyalty programs increases engagement, while interactive experiences such as personalized quizzes cater to individual preferences. Improved insights based on data gained from behavioral analytics and user segmentation are essential to improve your e-commerce strategy.

Improved customer journey mapping in e-commerce uses Omni channel integration and journey predictions to create a consistent shopping experience. Predictive analytics helps identify potential shopping cart abandonment, which enables businesses to offer personalized discounts that reward completed purchases. Real-time adaptability in e-commerce is powered by feedback loops and context awareness, allowing the system to respond to user needs and preferences. On the other hand, DL models use continuous learning to refine recommendations based on new user interactions and remain relevant despite changing market trends. Geolocation and time sensitivity enable companies to offer localized products tailored to the user`s climate or local events. Additionally, session-based recommendations allow the system to analyze live user sessions and instantly adjust product display to provide a more relevant shopping experience.

In the ethical consideration, the explanation is given to users how recommendations work builds trust and allows them to adjust their preferences, improving satisfaction. Offering an opt-in model gives users control over their data, building trust and fostering long-term relationships between consumers and brands. The table 3 summaries the core differences in traditional and AI- driven RS in the domain of e-commerce.

6. Future Directions

AI technology and ecommerce continuous to evolve, in future also holds prominent enhancement on it. The potential advancements of AI in the e-commerce sector hold the promise of transforming the industry. A crucial focus of innovation lies in enhancing natural language processing (NLP) algorithms, enabling AI to more effectively comprehend and address user inquiries. Enhancing language comprehension will boost the functionalities of RS, leading to more seamless and instinctive customer interactions. The figure 5 depicts the pictorial representation of the future trends in the AI-based recommendation system.

Table 3. *Core variation among traditional and AI- Recommendation system*

Aspects	Traditional Recommenders System	Recommender System with AI
Data Usage	Only validate with limited Data	Analyses vast amounts of data to provide personalized product suggestions
Filtering Algorithms	Content-based filtering and knowledge- based filtering	Content-based, Collaborative, and Integrated filtering that leverages ML and advanced techniques, to identify patterns and trends in user behavior.
Personalization	Limited to matching keywords or user history. Suggestions based on items similar to those the visitor is already viewing or the user's purchase history	Provide more accurate and personalized recommendations to customers. Considers factors such as holidays, geolocation, and semantics.
Content Discovery	Suggests content after users have already found similar item	Predicts user interests rather than suggesting content after users have already found similar items
Adaptability	Only matches keywords and follows assigned rules	Constantly learns and adapts, making the recommendations more precise and personalized
Theoretical contribution	It groups users based on their behaviour and past user interactions with items to generate recommendations	This uses advanced technologies like ML, DL, and NLP to study extensive data sets and user interactions in order to provide tailored suggestions. By identifying nuanced trends and adjusting to specific preferences, these systems offer suggestions that are more prominent than conventional approaches.
Practical Applications	Limited in helping visitors discover content. May not address the cold-start problem It has inability to recommend products outside a user's historical preferences.	Adapts in real-time based on a prospect or returning customer's interactions with an e-commerce website. Examples: (Amazon, Alibaba, Walmart, Flipkart, etc.)

1. **Advanced ML techniques:** The advancement of ML algorithms is predicted to result in more advanced capabilities, allowing e-commerce platforms to obtain a better understanding of consumer behavior and preferences [65]. This deeper understanding will improve the precision of personalized recommendations, leading to a more immersive and engaging user Furthermore, AI-powered image and video recognition technologies are expected to be crucial in enhancing visual search capabilities.

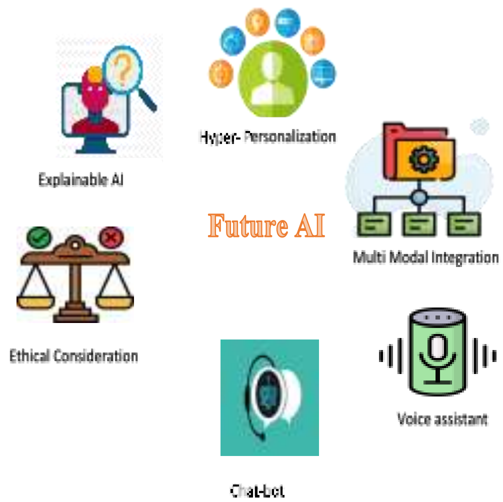

Figure 5. *The Future trends in Recommendation system*

2. **Enhanced Search ability:** Users will have the ability to search for products by uploading images or screenshots, fundamentally changing how they discover and shop for items online. Improved visual search functionalities could transform product discovery, making the shopping experience more intuitive [66].
3. **Improved visual recognition:** Furthermore, the future in ecommerce can be tend to enlarges by exploring synergies with AI and emerging advancements. Augmented Reality (AR) and Virtual Reality (VR) are set to merge with AI, resulting in immersive and interactive shopping experiences. Customers will have the ability to virtually try on products, visualize items in their homes, and interact with products in ways that surpass traditional online shopping methods. Additionally, blockchain technology is expected to enhance the security and transparency of e-commerce transactions. By utilizing a decentralized and tamper-proof ledger, blockchain can alleviate concerns regarding data security and trust in online transactions [67].
4. **Integration of AI with Internet of Things:** Moreover, the combination of AI with the Internet of Things (IoT) could foster a more

interconnected and intelligent e-commerce environment. Smart devices equipped with AI capabilities may enable seamless and context-aware shopping experiences, facilitating more personalized and efficient interactions between users and platforms [68].

5. **Hyper-Personalization**: AI models will use a variety of data sources, such as browsing history and live interactions, in order to provide personalized recommendations and customized shopping experiences.
6. **Voice & Conversational AI:** Conversational AI is transforming e-commerce by enabling personalized and real-time customer interactions through AI chatbots and voice assistants. The rise of voice assistants like Alexa, Siri, and Google Assistant makes conversational commerce essential for improved satisfaction and sales. Integrating this technology is crucial for future e-commerce success [69-72].
7. **Regulatory and ethical consideration:** Future AI based RSs need to make ethical practices and data transparency a top priority. The implementation should consider the regulations such as GDPR and CCPA, as well as worries regarding AI bias. Adherence to these regulations entails being open, just, and responsible in the collection, use, and safeguarding of customer data.

7. Conclusion

The review has conducted to investigate on IRS in e-commerce, highlights the pivotal role of ML and DL techniques in enhancing user experiences and boosting sales. As e-commerce evolves, these systems serve as essential tools for delivering personalized shopping experiences that cater to individual consumer preferences. A comprehensive search of key databases was conducted to gather relevant and high-quality research papers published from 2021 to 2025. It has analysed regarding the AI-driven recommendation models, key components in RS, various algorithms that leverages the personalization in RS and ethical challenges related to AI-powered RS model. Besides, it integrated recent academic writings, real-world examples, and hands-on experiences from leading online marketplaces such as Amazon, Walmart and Alibaba, with a focus on how AI techniques were used to improve customer satisfaction and operational efficiency. According to the analysis, the outcomes have shown that the most broadly utilized techniques in the field of AI-based recommender systems include Convolutional Neural Networks (CNN), Collaborative Filtering, sentiment analysis, Long Short-Term Memory (LSTM) networks, and Decision Trees. Additionally, the advanced AI technique known as BERT has demonstrated significant advancements in enhancing the effectiveness of RSs. Besides, it has revealed the significance of IRS to understand user preferences and interests on the product, to provide suggestion based on the browsing history. Hence, the effective IRS could increase revenue, boost sales and customer satisfaction in the field of ecommerce and related online business.

Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.
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