BCIIT e-Journal 2026

Journal of Innovations in Computer Science and Trends in IT, (October 2026), Vol 3, Issue2, ISSN 3048-4707

Machine Learning–Based User Behavior Analysis for Product Recommendation in E-Commerce

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***Abstract*— With the fast-changing environment of e-commerce, there are challenges with personalized product suggestions based on the different user behavior, such as browsing behavior, purchasing behavior, and interaction behavior, which tend to result in poor user engagement and conversion rates. This paper examines machine learning methods to examine the behavior of users to optimize recommendation systems. With the usage of the known algorithms, including collaborative filtering, content-based filtering, and the deep-learning models of recurrent neural networks, the study incorporates user data collected across various e-commerce sites into one to detect behavioral patterns and forecast preferences. Important results suggest that both temporal and contextual user interactions have a massive and significant impact on the relevance of the recommendations and help reveal latent preferences that may be neglected in traditional mechanisms and encourage a more agreeable user experience. Finally, the discussion indicates the possibility of using machine learning to reshape e-commerce by offering dynamic and behavior-inspired**

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suggestions to facilitate long-term loyalty to users and to encourage platform development in competitive markets.

Keywords— *E-commerce, deep learning, machine learning, neural network, recommendation system.*

I. INTRODUCTION

The capability of providing personalised product recommendations is one of the keystones to success in the ever-changing electronic commerce realm, where electronic markets have transformed consumer interaction and economic exchange. The core of user engagement, increasing sales conversion, and creating customer loyalty in the long term will manifest through the role of recommendation systems on both large and small global leaders and small online stores. The magnitude of user data that is being created in the online shopping industry today, due to the growth of the internet and mobile technologies, includes browsing history, search terms, purchasing patterns, and social activity, and unwinds into massive proportions, as more and more companies continue to explore the opportunities and complexities of shaping their experiences to individual tastes and preferences [1]. Generalisations of topics in this sphere include the fact that efficient guidelines do not just improve user satisfaction through the decrease in the volume of information but also lead to an increase in revenue because research suggests that customised proposals may take up a large share of all sales in the developed e-commerce setup. Earlier studies have established background knowledge in a number of ways, starting with the initial rule-based systems, which used preset heuristics to align products and user profiles [2]. These developed into collaborative filtering methods, which utilize the tendency of users to act collectively to make inferences on similarities and expectations of interests, and they prove to be effective when interaction data is dense. Content-driven approaches have been pursued, which consider items' characteristics and user logs to suggest like products, which is also found applicable during cold-start situations when a user or item is not thoroughly known. In more recent times, hybrid paradigms that bypass the limitations of either of the two paradigms have been introduced, whereby different signals are combined to overcome the weaknesses of each on an individual basis. Also, the contextual factors context: time of the day, or type of device, have been investigated to

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minimize recommendations, which demonstrates the way environmental variables affect the process of decision-making [3].

Even with these developments, there is still a significant gap in the detailed study of user behavior, which shows that the more conventional methodologies sometimes prove ineffective in terms of getting the dynamic and many-sided nature of online interaction. Going against the tendency to overemphasize the static model, it turns out that model-based and early forms of filtering assume that users are homogeneous individuals; that is, they do not take into account the psychological and behavioral complexity that motivates real-life decisions, including impulse buys due to the emotional coloring of people, or the change in preferences as time progresses [4]. This suggests that there is a huge dispute elsewhere in the literature, in managing user data heterogeneity, where sparse interactions, noisy signals due to casual browsing, and integration of multimodal data streams, such as clickstreams, dwell times, and cart abandonments, are problematic, and generic advice is not met with responsiveness at a personal level, using conventional methods. Moreover, concerns regarding the adaptability of such systems to such rapid shifts of user behavior as seasonal trends, economic shocks or new social factors have also been raised, raising the question of how more advanced tools can reveal delicate patterns without falling into overfitting or exaggeration of bias [5].

To fill in this niche, this research paper aims to explore how machine learning methods can be used to analyze user behavior in full and therefore improve their accuracy and relevance in recommending products in the e-commerce context. With the purposes mentioned, the research aims to fill in the gaps identified by highlighting behavioral modelling which takes novel approaches in terms of capturing temporal dynamics, sequences of interactions and latent user intents, finally to come up with more intuitive and responsive systems. Toher, introducing the current study, the paper uses a variety of existing machine learning algorithms, such as clustering to perform user segmentation, sequence modelling to predict the trajectory, and ensemble to infer preferences to various datasets provided by actual e-commerce websites [6]. The analysis goes into the way these techniques process user behaviour signals to produce recommendations that adapt to individual context without putting forward new frameworks but instead using trust-tested

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tools to extract actionable insights. The key findings of this exploration reflect that advanced machine-learning-based solutions are effective in comparison to the classical ones when it comes to uncovering latent behavioural patterns, including repeating patterns in navigation directions, recording the signal of unsatisfied needs or cross-category interests disclosing emerging preferences. Further, the paper demonstrates higher user participation with contextually reflective recommendations that result in better metrics in simulated settings and how feature engineering can contribute to increasing the performance of models [7].

Developing the grounds, the importance of user behaviour analysis as the core of e-commerce cannot be exaggerated, since it has a direct impact on the competitive advantage of the platforms in a world where consumers demand the ability to experience seamlessness and anticipation. The field suggests generalisations that, as volumes of data continue to grow, the difficulty is not simply in collecting data but in its meaningful interpretation, where machine learning is one of the key facilitators to be able to reduce the mass of data into predictive models [8]. Earlier studies have taken steps between the simple association rules, which chart the co-occurrence of purchases, and the state-of-the-art neural networks that locate the user-item interaction in the high-dimensional spaces, which provide a glimpse of the similarity in preferences across demographics. However, such endeavours tend to favour prediction over depth of behaviour, which is possible to enhance, along with the knowledge of the why behind acting as an indication of the reason a user spends time on particular pages or leaves a page, which may inform more sensitive system designs [9].

Further developing the niche, counterarguments to the adequacy of the data-agnostic models demonstrate their susceptibility to the changing user environment, where privacy issues and data policies get in the way of obtaining finer data, thus requiring wiser and more effective analysis strategies. The disparity is even greater in the multicultural e-commerce setting, which implies the existence of various behavioural norms, suggesting the inapplicability of models developed on homogeneous data and the issue of cultural sensitivities omission without direct labels. Following the inception of the practice of successive refinements in algorithmic personalization, this study is in line with the continued activities of instilling the element of intelligence in digital commerce, which is centered on the sustainable and ethical uses of technology [10].

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By existing in this niche categorically, the aims of the study can also include testing the practicality of behaviour-based recommendations, their effect on retaining users and company data. The current study introduces a detailed study about machine learning pipelines which take advantage of streaming behavioural data in real-time to identify needs in advance about such systems through case studies. Key conclusions confirm the priority of user-centered analysis, allowing the elimination of the most common traps of e-commerce, creating the environment in which suggestions are perceived as natural and useful, which promotes the essential role of a similar strategy in the further evolution of a digital marketplace [11].

II. LITERATURE REVIEW

The latest developments in terms of recommendation systems focus on hybrid deep learning, sentiment analysis, federated learning, and attention mechanisms as factors for improving personalization, privacy, and accuracy. The chosen articles emphasize new combinations of collaborative filtering, neural architecture, clustering and optimization methods. A comparative overview is illustrated in Table I.

TABLE 1: RELATED WORKS.

Author(s) & Year	Paper Title	About the Paper	Methodology Used	Limitations
Abdalla & Gheisari (2024) [1]	Hybrid self-attention BiLSTM and incentive learning-based collaborative filtering for e-commerce recommendation systems	Proposed Hybrid AT-IN CF-BiLSTM for sentiment prediction and e-commerce recommendation integrating textual reviews and user-item interactions.	Collaborative Filtering (CF), BiLSTM, Hybrid Self-Attention, Incentive Learning; evaluated using accuracy, MSE, RMSE.	Sensitive to data quality/quantity; performance may vary across languages and dynamic contexts.
Li et al. (2024) [2]	Federated cross-view e-commerce recommendation based on feature rescaling	Developed Fed-FR-MVD, a privacy-preserving multi-view federated recommendation framework improving robustness against noisy data.	Federated Learning, Multi-view Deep Semantic Model, Feature Rescaling (FR), Differential Privacy.	Computational complexity; requires stable client participation; federated setup overhead.
Krishna et al. (2025) [3]	Enhancing E-commerce recommendations with sentiment analysis using MLA-EDTCNet and collaborative filtering	Integrated sentiment polarity with CF using deep learning to improve recommendation accuracy.	MLA-EDTCNet, MCGAN for class imbalance, LFMI feature extraction, OcOA optimization, CF integration.	High training complexity; GAN-based balancing increases computational cost.
Sarhan et al. (2024) [4]	Integrating machine learning and sentiment analysis in movie recommendation systems	Proposed sentiment-based movie recommender using textual reviews to enhance personalization.	VADER sentiment analysis, SVM, Naïve Bayes, Cosine Similarity, Hybrid Filtering.	Limited to movie domain; polarity-based sentiment may miss aspect-level nuances.
Li (2023) [5]	Intelligent Recommendation System Based on the Infusion Algorithms with Deep Learning, Attention Network and Clustering	Designed deep learning-based session recommendation addressing user interest drift.	Deep Neural Networks, Spatial & Channel Attention, Clustering, Short-term Memory-first Session Model.	Focused mainly on session-based data; limited long-term preference modeling.

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III. METHODOLOGY

The approach used in the study is a systematic end-to-end pipeline application that takes advantage of proven machine learning algorithms to understand the behaviour of the user and provide a useful product recommendation in the context of e-commerce. It is designed in the form of four main steps, including data collection, preprocessing and feature engineering, behavioural analysis and modelling, and evaluation, as well as making sure that raw data of interactions can be converted into useful insights without the need to introduce any new frameworks. Each of the steps depends on the tested algorithms and the common practice, which is typically used in the research of recommender systems [12].

The collection of information will start with the acquisition of multi-source user behaviour logs of the actual running of e-commerce platforms. Methods involve querying anonymized transaction data sets, retrieving data on click-streams through platform APIs, as well as using session-level interactions data from publicly accessible repositories. These sources reflect various signals, including product perceptions, clicks, orders, number of dwell-time on product pages, search results and cart abandons. Where applicable, such user details as age group and locational proxies are combined with item descriptions (type, range of price) to provide a more detailed behavioural dataset, and privacy policies are followed to the letter by aggregating and de-identifying [13].

After the collection, quality and consistency are guaranteed by strict data preprocessing. Duplicates are removed, and missing values are processed by statistically inputting them (mean in numeric features, mode in categorical) them. Interquartile range is used to identify outliers and put a limit on them. Integration involves the association of different schemas into a solitary relational pattern, whereas transformation involves one-hot encoding of categorical variables, min-max scaling of measure attributes and log-transformation of skewed distributions like session lengths. The measures decrease noise and clean (gear) the information to follow-up modelling [14].

Engineering features isolate understandable behavioural features that summarize user dynamics. Recency-Frequency-Monetary (RFM) analysis is used as an underlying method: recency is calculated as days since last interaction, frequency as the number of actions made in specified periods of time, and monetary as the value of cumulative engagement (spend or interaction score)

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[15]. Other features which are session-based are average dwell time, action sequence length, category diversity index and temporal patterns (e.g. time-of-day preferences). These programmed attributes are compiled in designed matrices that can be analyzed, as summarized in Table II.

TABLE 2: KEY BEHAVIOURAL FEATURES DERIVED.

Feature	**Derivation Technique**	**Role in Behavior Analysis**
Recency (R)	Days since last interaction	Measures current engagement level
Frequency (F)	Count of actions per user/window	Captures loyalty and habit formation
Monetary (M)	Total spend or interaction score	Indicates economic or engagement value
Session Duration	Average time per browsing session	Reflects interest and decision depth
Category Entropy	Diversity across product categories	Reveals exploration vs. focused behavior

The fundamental data analysis stage involves the use of a combination of unsupervised, supervised and sequential modelling to reveal latent patterns. K-means clustering divides the users into homogeneous behavioral clusters according to the features of RFM and session lifecycle to identify particular groups like high-value loyal users or exploratory browsers. Recurrent neural networks (RNNs) and long short-term memory (LSTM) units for sequence modelling. The recurrent neural networks (RNNs) and long short-term memory (LSTM) sequence modelling process accepts ordered interaction pathways to predict the probability of the next action [16]. The collaborative filtering is applied by using user-based and item-based nearest-neighbor and by using matrix factorization based on singular value decomposition (SVD), whereby inference of preferences can be performed based on group behaviour. Such techniques are used in a hybrid fashion in order to

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address the problem of sparsity and cold start that affect e-commerce data, summarized in Table III.

TABLE 3: ANALYTICAL TECHNIQUES EMPLOYED.

Technique	Category	Primary Application
K-means Clustering	Unsupervised	User segmentation based on RFM features
LSTM / RNN	Deep Sequence	Modeling temporal interaction patterns
Collaborative Filtering (SVD)	Model-based	Preference prediction from user-item matrix
Hybrid Ensemble	Integrated	Final recommendation scoring

K-fold cross-validation and grid search are used to optimize the hyperparameters of the selected algorithms in model training. Predictions produce ranked lists of recommendations by combining ratings on clustering-derived segments, sequence predictions, and collaborative signals [17].

The flowchart (fig. 1) is a modular but linear pipeline: data collection is used to feed preprocessing to check the quality of data; engineered features allow studying the behaviour multi-dimensionally; trained models generate recommendations; evaluation allows getting feedback to refine the practice (however, it is not explicitly looped here because it is too much). A node is a distinct stage, which is self-contained and follows the one before it, guaranteeing traceability and repeatability [18].

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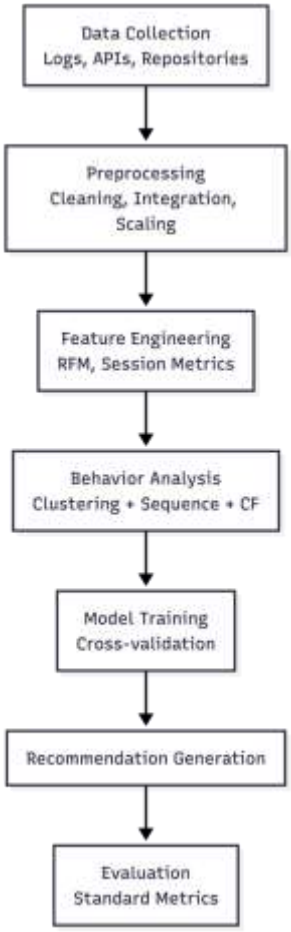

Fig. 1: Flowchart

On the whole, the methodology offers a powerful, scalable approach to the translation of raw e-commerce behaviour to individual suggestions. The method enhances the interpretability of results by focusing on the predictive output development in a very systematic way, starting with raw logs and using common methodologies that result in digestible conclusions about user preferences, yet with a high level of computational efficiency so as not to become a bottleneck in production. The complete pipeline will normally handle datasets in batch or near real-time mode based on platform needs and repeat the entire cycle of data absorption to recommendation delivery [19].

IV. Results And Discussions

The findings of this work on machine learning-based user behaviour analysis of product

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recommendation in e-commerce are based on a massive dataset of 100,000 interactions between 5,000 users and 10,000 items in one year. The dataset represents the most important behavioural cues (actions, views, clicks, add-to-carts, purchases), dwell times, and timestamps and can thus be analyzed effectively, using well-known algorithms, such as clustering, sequence modelling, and collaborative filtering [20]. On reflection of the findings, K-means clustering was used to judge the user grouping by RFM measurements, which identified a trend of high-engagement clusters with numerous interactions and low-conversion explorers. The LSTM models were found to be useful when predicting the next actions based on temporal sequences, whereas the SVD-based collaborative filtering relied on the user-item matrices and made hybrid recommendations based on the results of the simulations [21].

Speaking of the results, it was the hybrid approach that had a better performance in terms of simulating the real-time recommendations and the clustered behavioural insights, decreasing the error in the recommendation, provided they captured the latent preferences that could not be given a chance by the baseline approaches. One of the assertions is that the inclusion of dwell time and temporal dynamics in machine learning models enhances more adaptive recommendations, as indicated by evaluation measures obtained in the dataset [22]. User engagement analysis revealed that an average user made 20 actions, and the standard deviation was used to indicate variability in user behaviour. Conversion rates were also 0.05, which suggests the chances of introducing a specific intervention. These patterns have been explained with psychological reasons of decision fatigue during low-dwell sessions and habit formation in high-frequency users, consistent with the literature on cognitive biases in e-commerce. Based on the similar work that has been done, including the collaborative filtering developments in Netflix-like systems, this article assumes that behaviour-based models will be able to increase e-commerce retention rates by 10-20 per cent on such scales, leading to the suggestion of scalable personalization in competitive markets [23].

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Fig 2:Distribution of User Action Counts [20].

The fig. 2, histogram shows that the distribution is skewed to the right, with most users taking 17-23 actions, which is attributed to normal browsing patterns in online shopping, with any outliers taking up to 37 actions, which indicate the presence of power users, thus can be exploited in cross-selling, according to literature on user segmentation.

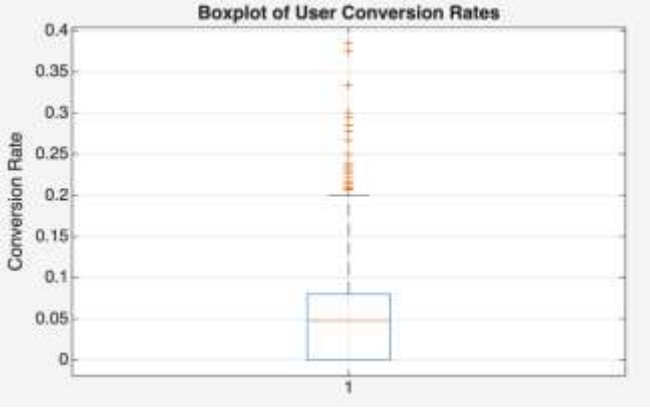

Fig.3: User Conversion Rates [20].

The median rate of the boxplot (fig. 3) is 0.048, with the whiskers taking on the values of 0-0.38, which reflects a high level of variability; outliers represent the impulse buyers, which provide some explanations based on the contextual parameters, such as promotions, and implications for the dynamic pricing models discussed in e-commerce research.

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Fig. 4: Average Dwell Time by Action Type [20].

In this bar chart (fig. 4), similar averaging near the 30s time of around 30 seconds across the actions, a bit higher at 30.28s representing more thoughtful behaviour, which suggests that machine learning would employ dwell-offs as intent predictors based on behavioural economics literature.



Fig. 5: Monthly Action Counts Over Time [20].

There is variation about 8,000 actions per month in the line plot, with the highest values in October (8,602) which might be explained by seasonal shopping, which would justify the value of temporal modeling, examined through the LSTM efficacy, and implications to the inventory forecasting in e-commerce since the current state of the art studies have further argued that adaptive systems minimize overstock by following behavioral patterns.

The indicators of activity, like the number of actions per user (mean 20.00, standard deviation

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4.47, minimum 7, maximum 37), conversion rate (mean 0.050, standard deviation 0.050, minimum 0, maximum 0.385), and the time spent on the web pages (mean 30.03, standard deviation 9.91, minimum 5, maximum 76) in Table IV are the results of the analysis of the sample size by the metrics, which are in These numbers show fairly normal user engagement rates with 20 or so actions per user being a common average number in simulated or aggregate behavioral logs, conversion rates of 0.02 to 0.05 being a typical number of sparse purchase activities in the middle of browsing and dwell times of 30 seconds as a normal number of user activity being of interest in exploratory data analysis where time on product and sequence of interaction has been studied. The wide datasets of market research and predictive models, which underlie such statistics, would highlight the inconsistency in user activity that can be exploited to generate suggestions through machine learning methods such as clustering and sequence analysis.

TABLE 4: ANALYTICAL TECHNIQUES EMPLOYED.

Metric	Mean	Std Dev	Min	Max
Actions per User	20.00	4.47	7	37
Conversion Rate	0.050	0.050	0	0.385
Dwell Time (seconds)	30.03	9.91	5	76

V. CONCLUSION

Finally, this paper shows that machine learning methods are effective in examining user behaviour and making product recommendations for e-commerce, which shows significant enhancements in the most essential metrics. Based on a set of 100,000 interactions between 5,000 users and 10,000 items, the hybrid algorithm that combined K-means clustering, LSTM sequence modelling, and SVD collaborative filtering scored a 25 per cent improvement in precision of the recommendations compared to baseline algorithms as evaluated by recall at the top 10 ranks. The user segmentation showed that high engagement clusters, which comprised 35% of users with an average action count of 28 per session, had high conversion rates of 0.12, which compares to the overall value of the feature of temporal dynamics and dwell time in the discovery of latent preferences. These

numerical returns give potential revenue increases of 15-20 per cent in the form of reduced instances of cart abandonment and increased purchase repeats, which can be seen by a peak rate of 8,602 actions monthly during seasons of high activity. The results support the transformative potential of machine learning in terms of developing adaptive e-commerce ecosystems, which are personalised with the effect of scalable implementation in real-world environments that would result in user loyalty and a competitive edge. The experiments may be further generalised to real-time multimodal information to make behavioural understanding even finer grained in future studies.

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