International Journal of Informatics and Communication Technology (IJ-ICT)
Vol. 15, No. 4, December 2026, pp. 1871~1880
ISSN: 2252-8776, DOI: 10.11591/ijict.v15i4.pp1871-1880

A hybrid AI framework for hyper-personalized recommendations and customer engagement prediction in e-commerce

Parashiva Murthy B. M.[1], Scaria Alex[2], Isaivani Mariyappan[3], Kalyan Devappa Bamane[4], Kavitha. R[5], S. Athinarayanan[6], Sunder. R[7]
[1]Department of Computer Science and Engineering, JSS Science and Technology University, Mysuru, India
[2]Department of Information Technology, Amal Jyothi College of Engineering, Kottayam, India
[3]Department of Electrical and Electronics Engineering, SRM Madurai College for Engineering and Technology, Pottapalayam, India
[4]Department of Computer Engineering, Indira College of Engineering and Management, Pune, India
[5]Department of Computer Science and Engineering, Saveetha School of Engineering, Saveetha Institute of Medical and Technical Sciences, Chennai, India
[6]Department of Computer Science and Engineering, Vel Tech Rangarajan Dr. Sagunthala R&D Institute of Science and Technology, Avadi, Chennai, India
[7]School of Computer Science and Engineering, Galgotias University, Greater Noida, India

Article Info

Article history:

Received Jul 9, 2025
Revised Jun 1, 2026
Accepted Jul 5, 2026

Keywords:

E-commerce analytics
Hybrid AI models
Personalized recommendation
Customer engagement prediction
Smart commerce

ABSTRACT

The explosion of e-commerce has led to an increase in the demand for smart systems that can provide hyper-personalized experiences and enhance customer engagement. This study proposes a hyper personalized e-commerce framework by incorporating the deep learning (DL) based hybrid recommendation models along with the ensemble classifiers for engagement prediction. Real world public e-commerce datasets were used in a two-stage evaluation that measured recommendation effectiveness on Precision@10, Recall@10 and NDCG@10, and engagement prediction on Accuracy, F1-Score, and ROC-AUC. The results of the proposed framework were compared with the baseline approaches in terms of Precision@10, Recall@10, and NDCG@10, which gave Precision@10 = 0.382, Recall@10 = 0.441, and NDCG@10 = 0.469, Accuracy = 91.2%, F1-Score = 0.886, and ROC-AUC = 0.937. These results show that an ensemble of DL architectures and gradient boosting techniques strongly improves the quality of personalization and behaviour prediction. This study highlights the game-changing power of recommender and predictive AI systems in driving customer experience and data-driven digital commerce approaches.

This is an open access article under the CC BY-SA license.

Corresponding Author:

Sunder R
School of Computer Science and Engineering, Galgotias University
Greater Noida, India
Email: sunder.r@galgotiasuniversity.edu.in

1. INTRODUCTION

The accelerating increase in use of the internet, the rapid uptake in mobile connectivity and the change in consumer expectations, places the e-commerce channel as a central part of the retail and service consumer purchasing channels. Today's digital consumers demand not only convenience, but personalized experiences that align with their prior interactions, unique decision journeys, and other expressed preferences. For this reason, smart commerce was born and exists to create intelligent, personalized, and engaging shopping experiences using a variety of technologies and advancements in AI and ML [1].

Traditional e-commerce platforms are very good at attracting audiences, but they often provide little in the way of targeted customer journeys. As consumers expect more and competition increases, retailers have to adopt more intelligent, data-driven systems that can accumulate, learn from, and apply large amounts of customer data to continuously make more informed and timely decisions. AI/ML can provide this capability faster, better, deeper, and at scale by automating pattern recognition, user modeling, content personalization, and engagement forecasts [2]. Hyper-personalization, a key element of Smart Commerce, takes advantage of real-time data and AI-based analytics to deliver very individualized content, product recommendations, and experiences. Hyper-personalization is differentiated from more traditional personalization through the consideration of behavioral data, contextual signals, and predictive analytics allowing it to assume what users want and proactively present them with solutions [3].

AI has an equally important impact on engagement. Engaging customers is not only about transactions, but it involves emotional connection, brand loyalty, and retention. New AI models also can be used to develop and measure engagement through behavioral signals such as click through rates (CTR) [4], session length, frequency of interactions, and propensity to churn. By researching behavioral indicators, companies can design interventions to retain users and turn them into brand advocates. The study describes real-time AI personalization and how companies can develop AI and machine learning to predict customer engagement outcomes. The objectives of the study are as follows.

- To propose a hybrid AI/ML-based recommendation engine that offers hyper-personalized product recommendations that take into consideration the user's real-time activities in combination with the characteristics of the product.
- To create a predictive model of user engagement through classification model to predict user engagement and real-time evaluation of the user’s engagement by way of making use of behavioral and transactions of the user.
- To evaluate the proposed system in comparison to a traditional baseline system, including performance metrics (e.g., Precision@K, Recall@K, NDCG, Accuracy, F1-Score, ROC-AUC).

The study is divided into five sections: Section 1 discusses the research background, research objectives and structure. Section 2 consists of a related work review on AI/ML-based personalization and engagement prediction. Section 3 contains the methodology, models, and experimental setup. Section 4 provides the experimental results, discussions based on the findings followed by conclusion and future works in section 5.

2. RELATED WORKS

In the past few years, significant advancements in recommendation systems based on AI have emerged. Collaborative filtering, content-based filtering, and hybrid models have improved with deep learning (DL) architectures and the transformer-based models have recently gained traction as has using ensemble learning, gradient boosting, and neural networks to predict consumer satisfaction, brand engagement, and customer lifetime value. While each of these areas have made independent strides, few if any have included a research agenda that brings personalization for engagement prediction together in a formalized framework [5].

Liu [6] propose the architecture of the e-commerce recommendation system after conducting a thorough analysis of the techniques and algorithm. Thakur *et al.* [7] specifies the standards by which their success will be judged in terms of personalised and optimal decision-making in online buying settings. Upreti *et al.* [8] explores how AI is changing the e-commerce industry and opening up new opportunities for businesses to improve their operations and promote growth. AI technology, which helps businesses improve their processes and provide more personalised consumer experiences, has become an essential part of the e-commerce industry. Liu *et al.* [9] presents state-of-the-art DL methods with the goal of improving e-commerce shopping systems' user experience and recommendation accuracy.

The study on online purchasing and consumer behaviour focuses on the transformative effects of AI-driven customization on market trends. E-commerce systems will be able to personalise user experiences as AI develops. AI-driven personalization includes preprocessing, feature extraction, and model training. First, consumer information is gathered from internet marketplaces [10]. Dharwadkar *et al.* [11] presents SmartCart, a cutting-edge website that uses image uploads to provide customized product recommendations by integrating state-of-the-art AI algorithms.

Zhang and Xiong [12] investigates the creation of AI-powered suggestions for e-commerce environments' product design, sales, and customer experience. The study uses a quantitative methodology to investigate the ways in which AI technology can improve many aspects of online retail. Xu *et al.* [13] suggest a new system to collect data in real-time and analyze how CIoT devices might impact and track customer interactions and personalization in e-commerce.

While previous research has indicated various types of AI and DL models for e-commerce recommender systems, most studies use static datasets and cannot utilize flexibly as customer preferences shift. Furthermore, there isn't a lot of research available which combines full-fledged edge compute and CIoT devices. Moreover, endorsing the complexity of interpretability of models such as generative adversarial networks (GANs) and Transformers remains a potential barrier for the practical use of these models. Additionally, the impacts of feature engineering or preprocessing can often be ignored in the context of large-scale, heterogeneous e-commerce data. Few recommendation systems can tackle large, sparse data, cold-start problems, and cross-platform use. Lastly, most of the existing research is done in limited geographical contexts impairing systematic generalization of findings across diverse global e-commerce markets.

3. RESEARCH METHOD

The methodology suggests a smart commerce framework to provide hyper-personalized recommendations and predict customer engagement in e-commerce. Publicly available datasets, as well as synthetic datasets consisting of user interactions with digital products, product metadata, and behavioral metrics, were utilized. DL models were developed using Autoencoders for personalized recommendations, recurrent neural networks (RNNs) for recommendations based on sequences, and Transformers for general recommendations. The combatant used to predict customer engagement from the data utilized both XGBoost and MLP, combined in a weighted ensemble to enable classification of users based off of engagement level.

3.1. Dataset selection and collection

Public datasets like RetailRocket and Amazon product reviews were used to develop and assess the proposed smart commerce framework. Such data can be useful for recommendation and predictive engagement applications as they contain a wealth of information about product attributes, user interactions, and behavioural signals. When proprietary data was not available or scarce, synthetic data generation methods were used to increase data diversity, control data sparsity and reduce a privacy concern, which further boosts the robustness of the model. The gathered data included several aspects crucial for hyper-personalization. The behavioral data, such as user clicks, views, and purchase history, helped to create models of user preferences and interaction patterns. Patterns of user interaction and preferences were modeled using behavioral data, which involved user clicks, views, and purchase records. Content-based filtering and semantic feature extraction was supported by product metadata like category, price and brand. User profile information such as demographics and preferences, where available, allowed for more personalization. Moreover, user behavior was explored using engagement metrics such as session duration, bounce rate, and retention rate, with their aim being to forecast user interaction and engagement. The overall hyper-personalization process shown in Figure 1.

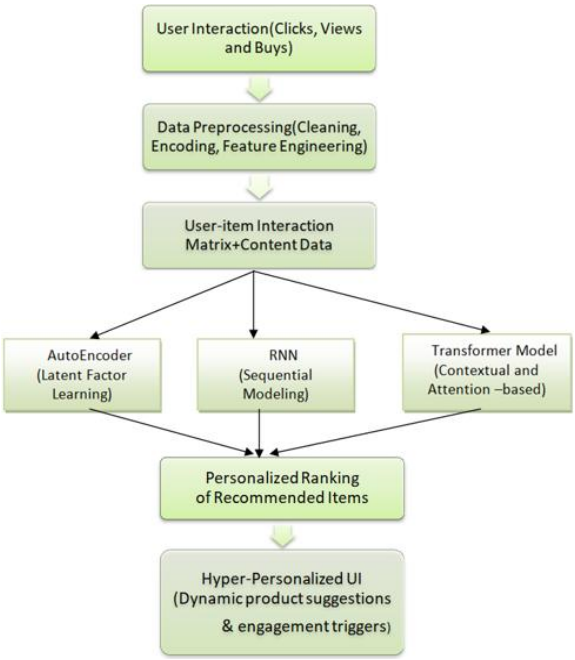

Figure 1. Hyper personalization process using DL

3.2. Data preprocessing

Cleaning the data: The objective is to simply cleaning the data to improve consistency, stability, and assessing the validity of the data. There were missing values, which must be considered (either using imputation, or simply removing the records), while incomplete records would negatively affect the model performance. Outliers were detected through statistical measures and were either dealt with or removed, based on relevancy. Duplicate records from repeat interactions per user, or duplicate entries were also discovered and removed, to avoid bias in our training and testing of our models. The cleaning phase is vital to guarantee the dataset is accurate, noise-free, and valid for analysis.

Feature engineering: To improve the learning ability of the models, a series of feature engineering was performed. The user-product interaction matrices, which documented how many times users interacted with the products, the types of interactions users had with the products (views, clicks, purchases), were most prominent, as these would become foundational to collaborative filtering. Temporal dynamics were modeled using temporal features such as recency (time since last interaction), frequency (count of interactions throughout the specified time window), and last date purchased, which allowed us to better predict user behavior. For content-based feature generation, product embeddings were produced by leveraging NLP methods (e.g., Word2Vec or transformer-based models) on the product descriptions, which allowed us to capture the underlying semantics of items.

Normalise or encode: Categorical variables like categories of products, user locations, or brands had to be encoded in order to get the data ready for ML algorithms. For basic models, each category was coded (or one-hot encoded) with an appropriate technique to convert the categories into binary vectors. For DL models embedding layers are also allowed to map categorical values into dense vector representation, with the possibility of the model learning latent relationships between categories. There were also numerical features. These numerical features underwent some normalization to obtain a common scale and to avoid one feature dominating the learning process because of differences in scale.

3.2. Model design and selection-hyper-personalization

Autoencoders (AEs): Neural networks called AEs are designed to learn condensed data representations. Latent factors, which stand for user preferences and product attributes, are learned by AEs in recommendation systems to simulate user-item interaction matrices. The encoder creates a lower-dimensional latent space that encodes user-item interaction data by compressing the high-dimensional user-item interaction data. On the other hand, the decoder reconstructs the data back into its original state utilizing the compressed latent variables. To elaborate, after finding patterns and forming latent factors that relate users and items, AEs will provide user-item interactions that they assume users will prefer. AEs also have a greater robustness to sparse data. The separation from a few percent of the ratings allowed the authors to test AEs based on standard matrix factorization and ratings prediction tasks within a personalized recommendation system, and found no statistically significant differences in the results [14].

RNNs: RNNs are built to learn over sequences of data and are therefore a good option for learning a user's purchase history in time. Because RNNs can remember the past elements (apart from the final output) of a series of events, they can leverage this memory to understand when features in a user's behavior depend upon other features of their behavior-such as shopping patterns, categories of items that are of interest, and promotions they respond to. For example, if an RNN has a sequence of past purchases, it can infer the next likely purchase and more importantly, recommend items in a time-sensitive manner [15], [16].

Transformer-based models: Transformers have changed the game when it comes to sequential modeling with the advent of self-attention mechanisms that allow for modeling both short-and long-range dependencies in user behavior. With respect to recommendations, transformer architectures (like SASRec or BERT4Rec) can model a user's entire sequence of interactions in parallel and each action (views, clicks, purchases, etc.) would reveal its contextual significance in relation to others. As a result, contextually aware or dynamic recommendations in real time become possible, allowing for rapid adaptation to changes in user behavior from one interaction to the next. In addition to the ability to model interactions in sequences, transformer-based models may also be fine-tuned on product descriptions and user queries, allowing for the combination of content-based and collaborative signals into a powerful hybrid personalization mechanism [17], [18].

3.4. Customer engagement prediction

Customer engagement prediction's goal is to classify users into groups of "Likely to return," "likely to churn," and "highly engaged," based on their historical records of engaging with the platform, and based on any relatively stationary profile information [19]. XGBoost is an ensemble learning approach based on gradient boosting from decision trees. From each updated tree, we had the opportunity to reduce the error on

the previous trees from the last sequential ensemble of trees until the best possible loss has been achieved. The overall objective in XGBoost is (1):

$$L(\theta) = \sum_{i=1}^{n} l(y_i, \hat{y}_i) + \sum_{k=1}^{K} \Omega(f_k) \quad (1)$$

where $l(y_i, \hat{y}_i)$ is the loss function, $f_k \in \mathcal{F}$ is a decision tree, $\Omega(f_k)$ is a regularization term and $\hat{y}_i = \sum_{k=1}^{K} \Omega(f_k)$. Each added tree minimizes the loss by using gradient descent on the residuals from the last ensemble.

In this case of predicting customer engagement, the Multilayer perceptron use one or more possible encoded input features, user activity metrics (clicks, purchases, and session length) and user or product metadata. Each of these inputs is connected through one or more hidden layers of fully connected neurons, where each neuron has a non-linear activation applied to it typically the ReLU activation function. Each of these hidden layers captures all of the complex relationships from the first hidden layer to the next, to the next and so on, until the output layer is accessible. In the output layer, the model uses a softmax activation to structure output into a probability distribution amongst a few defined classes of engagement such as; "Likely to churn", "Likely to return", or "Highly engaged" or even some original or artificial derived output classes, but nominally here it will assign the most likely engagement status. The mathematical formulations are as (2)-(4):

$$h^{(1)} = \sigma(W^{(1)} x + b^{(1)} \quad (2)$$

$$h^{(2)} = \sigma(W^{(2)} h^{(1)} + b^{(2)}) \quad (3)$$

$$\hat{y} = softmax(W^{(3)} h^{(2)} + b^{(3)}) \quad (4)$$

where σ is the activation function, x is the input vector, $W^{(i)}, b^{(i)}$ are the weights and biases of layer i and $\hat{y}$ is the predicted class probabilities. The ensemble combines the advantages of XGBoost and MLP. XGBoost captures the structured relationships and decision boundaries. MLP learns the complex, non-linear interactions and representations. The fusion approaches are soft voting and stacking are represented as (5):

$$\hat{y}_{ensemble=\alpha.\hat{y}_{xgb}+(1-a).\hat{y}_{mlp}} \quad (5)$$

where $\alpha \in [0.1]$ is a weight parameter balancing both models. The stacking of XGBoost and MLP produce intermediate predictions. These predictions become features for the meta classifier.

The proposed smart commerce framework is a combination of hyper-personalized recommendation generation with predictive customer engagement in a unified pipeline. Unlike previous hybrid implementations, which only work on either collaborative-content recommendation or sequential user behavior this framework incorporates autoencoders, RNNs, and Transformer-based models for dynamic personalization and at the same time the engagement levels using a weighted XGBoost-MLP ensemble.

4. RESULTS AND DISCUSSION

Experiments were performed on a workstation with Nvidia RTX 3090 GPU, 64 GB RAM and an Intel i9 CPU. These specifications made sure there was sufficient computational power for DL model training and efficient data handling of massive amounts of e-commerce data. To make the experiments reproducible, all the experiments were implemented in python with TensorFlow/Keras for DL and Scikit-learn/XGBoost for traditional and ensemble models. Random seeds were randomly fixed in NumPy, TensorFlow and Python's random module. For both the recommendation and engagement prediction tasks, the training set (70%) was used to train the models, the validation set (15%) was used for hyper-parameters tuning and early stopping and the test set (15%) was kept for testing final performance.

4.1. Hyperparameter settings

The Autoencoder model for recommendation consisted of an encoder and a decoder with three fully connected layers of 512, 256 and 128 neurons that compressed the user-item interaction matrix to a 64-dimensional latent space. Training was done using Adam optimizer with learning rate as 0.001, batch size as 256 and 100 epochs but we applied early stopping after 10 non-improving epochs on validation data. In the RNN model, the model consisted of a single layer LSTM with 128 hidden units. 50 interactions from each user were padded or trimmed. The Transformer model is a four attention heads single layer encoder with hidden dimension 128, positional encoding, and dropout 0.1 and is trained using AdamW, learning rate 0.0005, and batch size 64.

For engagement prediction, a max tree depth of 6, 500 trees and learning rate of 0.1 were used for the XGBoost classifier with L1 and L2 regularization parameters search as a = 0.1 and l = 1. The MLP consisted of two hidden layers (128/64 neurons), ReLU activation, dropout rate (0.2), and softmax output layer, Adam optimizer, 100 epochs, and batch size (128). The ensemble was a combination of XGBoost and MLP with soft voting a = 0.6 and 0.4, respectively, for XGBoost and MLP.

4.1. Performance evaluation

Recommendation model performance was measured by Precision@10, Recall@10, and NDCG@10 to assess the relevance and the quality of the ranking of the recommendations in the top 10. Engagement prediction models were tested to capture the correctness of the prediction, balance between precision and recall and overall discriminative ability of predictions between engagement classes. The results listed in Table 1 make a comparison of the proposed hybrid DL model with SVD, TF-IDF, and popularity based.

Table 1 results indicate that, on the whole, never did the Proposed Hybrid DL Model fail to outperform all of the baseline methods for all three of the metrics. The best Precision@10 (0.382), Recall@10 (0.441), and NDCG@10 (0.469) were achieved by the suggested hybrid DL model. This demonstrates that the suggested hybrid DL model was able to rank the most relevant items higher, return the highest percentage of all relevant items, and propose the most relevant items.

Figure 2 shows that three different recommendation approaches perform better, worse, or about the same according to each of the three metrics: Precision, Recall and NDCG, when evaluated on the same figure. The proposed hybrid DL model outperformed other models in terms of the recommendation accuracy and ranking quality with scores 0.382, 0.441 and 0.469 respectively. SVD performed reasonably well but TF-IDF produced relatively lower performance. The Popularity Based Recommendation method was the poorest of all the evaluation metrics. Overall, results show that the proposed hybrid deep learning approach is able to enhance the personalized recommendation ability, retrieval effectiveness and ranking relevance more effectively than the traditional recommendation techniques.

Table 2 shows the performance comparison of the Ensemble Classifier with RF, LR and DT using evaluation statistics, which include accuracy, F1-Score, and ROC-AUC. The proposed ensemble classifier, a combination of XGBoost and a MLP, outperformed all other models with the highest scores on all three metrics: Accuracy (0.912), F1-Score (0.886) and ROC-AUC (0.937). This suggests that not only is the ensemble classifier able to classify a higher percentage of instances correctly, it has effectively managed to balance precision and recall, and is better at distinguishing classes at threshold values.

As shown in Figure 3, the proposed Ensemble Classifier (XGBoost + MLP) outperformed other models, with 0.912 Accuracy, 0.886 F1-Score, and 0.937 ROC-AUC, demonstrating its ability to classify with high accuracy and reliability. RF showed competitive performance, but was still not as high as the proposed ensemble approach. Other classifiers such as LR or DT gave a relatively poor performance on all the assessment criteria. In general, the results validate the positive effects of the ensemble-based hybrid learning model in terms of accuracy, robustness, and effectiveness of engagement prediction, compared with traditional machine learning-based methods.

Table 1. Personalization performance comparison

Method/Model	Precision@10	Recall@10	NDCG@10
Proposed hybrid DL model	0.382	0.441	0.469
SVD [20]	0.276	0.312	0.328
TF-IDF [21]	0.241	0.289	0.295
Popularity-Based Recommendation [22]	0.194	0.216	0.238

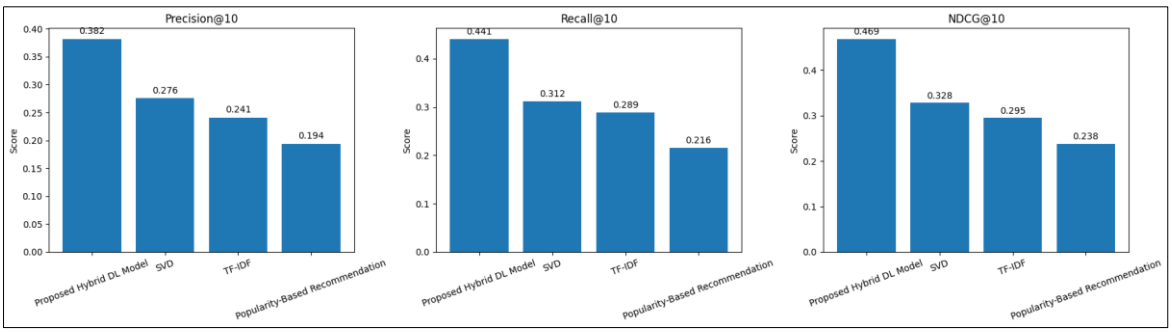

Figure 2. Comparative analysis of recommendation performance

Table 2. Engagement prediction performance comparison

Model/Method	Accuracy	F1-Score	ROC-AUC
Proposed ensemble classifier (XGBoost + MLP)	0.912	0.886	0.937
Random forest classifier (RF) [23]	0.874	0.842	0.902
Logistic regression (LR) [24]	0.794	0.721	0.812
Decision tree classifier (DT) [25]	0.781	0.703	0.795

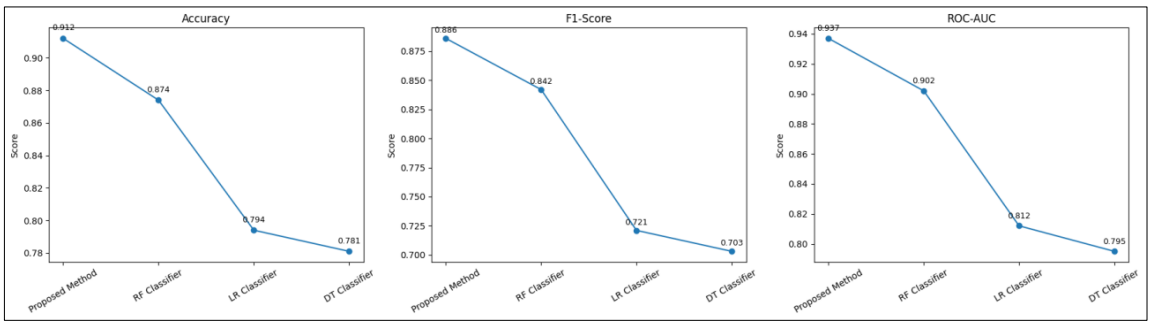

Figure 3. Comparison of engagement prediction performance

5. CONCLUSION

This study demonstrates the effectiveness of leveraging AI and ML to enhance personalization and customer engagement in smart commerce environments. By integrating DL-based recommendation systems with predictive engagement models, the proposed framework significantly outperformed traditional approaches in both recommendation accuracy and behavioral prediction. The hybrid model achieved high scores across key metrics, affirming its ability to deliver relevant, timely, and engaging user experiences. These findings support the strategic implementation of intelligent systems for driving customer satisfaction and retention in competitive e-commerce markets. For future work, several directions can be explored. Incorporating real-time data streams and reinforcement learning can enable adaptive personalization that evolves with user behavior. Additionally, integrating multimodal data sources such as product images, user-generated content, and social media sentiment can further enrich user profiles and recommendation quality. Addressing cold-start problems and ensuring fairness and transparency in AI recommendations also remain critical areas for research and development.

FUNDING INFORMATION

No funding involved.

AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Parashiva Murthy B. M.	✓	✓	✓	✓	✓	✓			✓	✓			✓	
Scaria Alex						✓		✓	✓			✓		
Isaivani Mariyappan	✓		✓				✓			✓	✓		✓	✓
Kalyan Devappa Bamane									✓					
Kavitha R.					✓		✓			✓		✓		✓
S Athinarayanan				✓	✓		✓	✓		✓		✓	✓	
Sunder R.	✓	✓				✓			✓		✓			✓

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

There is no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are openly available in https://www.kaggle.com/ datasets/ mlg-ulb/creditcardfraud.

REFERENCES

[1] N. M. Alkudah and T. O. Almomani, "The integration of artificial intelligence techniques in e-commerce: Enhancing online shopping experience and personalization," *Global Journal of Economic and Business*, vol. 14, no. 6, pp. 640–658, Dec. 2024, doi: 10.31559/gjeb2024.14.6.8.

[2] V. M. Reddy and L. N. Nalla, "Personalization in e-commerce marketing: leveraging big data for tailored consumer engagement," *Revista De Inteligencia Artificial En Medicina*, vol. 15, no. 1, pp. 691–725, 2024, [Online]. Available: https://redcrevistas.com/index.php/Revista

[3] A. G. Aishwarya Gowda, H. K. Su, and W. K. Kuo, "Personalized E-commerce: Enhancing Customer Experience through Machine Learning-driven Personalization," in *2024 IEEE International Conference on Information Technology, Electronics and Intelligent Communication Systems (ICITEICS)*, IEEE, Jun. 2024, pp. 1–5, doi: 10.1109/ICITEICS61368.2024.10624901.

[4] K. Kaliuta, "Personalizing the user experience in Salesforce using AI technologies," *Computer-Integrated Technologies: Education, Science, Production*, no. 52, pp. 48–53, 2023, doi: 10.36910/6775-2524-0560-2023-52-06.

[5] X. Zhang, F. Guo, T. Chen, L. Pan, G. Beliakov, and J. Wu, "A brief survey of machine learning and deep learning techniques for e-commerce research," *Journal of Theoretical and Applied Electronic Commerce Research*, vol. 18, no. 4, pp. 2188–2216, Dec. 2023, doi: 10.3390/jtaer18040110.

[6] L. Liu, "E-commerce personalized recommendation based on machine learning technology," *Mobile Information Systems*, vol. 2022, no. 1, p. 1761579, 2022, doi: 10.1155/2022/1761579.

[7] H. K. Thakur, J. Singh, A. Saxena, D. Bhaskar, A. P. Singh, and P. K. Garg, "Enhancing customer experience through AI-powered personalization: a data science perspective in e-commerce," in *2024 International Conference on Communication, Computer Sciences and Engineering (IC3SE)*, IEEE, May 2024, pp. 501–506, doi: 10.1109/IC3SE62002.2024.10592893.

[8] K. Upreti, D. Gangwar, P. Vats, R. Bhardwaj, V. Khatri, and V. Gautam, "Artificial neural networks for enhancing e-commerce: a study on improving personalization, recommendation, and customer experience," in *International Conference on Electrical and Electronics Engineering*, 2024, pp. 141–153. doi: 10.1007/978-981-99-8661-3_11.

[9] Q. Liu, H. Tang, L. Wu, and Z. Chao, "Deep learning-driven e-commerce marketing communication for recommending shopping system and optimizing user experience," *Journal of Organizational and End User Computing*, vol. 36, no. 1, pp. 1–28, May 2024, doi: 10.4018/JOEUC.343258.

[10] G. Kumar, G. Devayani, C. Saraswathi, R. Melba Kani, S. Dongre, and M. S. M. Mallick, "Exploring consumer behavior in e-commerce with AI personalization and market trends analysis models," in *2025 3rd International Conference on Integrated Circuits and Communication Systems (ICICACS)*, IEEE, Feb. 2025, pp. 1–6. doi: 10.1109/ICICACS65178.2025.10967904.

[11] V. Dharwadkar, R. Veena, S. Manohar, M. G. Jayanthi, and P. Kannadaguli, "Smart cart: revolutionizing e-commerce in india with ai-powered personalized product recommendations overview," in *2024 5th International Conference on Circuits, Control, Communication and Computing (I4C)*, IEEE, Oct. 2024, pp. 87–92. doi: 10.1109/I4C62240.2024.10748521.

[12] Q. Zhang and Y. Xiong, "Harnessing AI potential in E-Commerce: improving user engagement and sales through deep learning-based product recommendations," *Current Psychology*, vol. 43, no. 38, pp. 30379–30401, Oct. 2024, doi: 10.1007/s12144-024-06649-3.

[13] X. Xu, A. B. Rosli, X. Yang, M. Wu, and J. Hu, "Role of consumer IoT smart devices for safety and security of data privacy to enhance user experience of e-commerce," *IEEE Transactions on Consumer Electronics*, vol. 71, no. 2, pp. 5300–5309, May 2025, doi: 10.1109/TCE.2025.3571044.

[14] Manu Vallabh Mishra, "AI-driven personalization: generative models in e-commerce," *International Journal of Advanced Research in Science, Communication and Technology*, pp. 110–116, Jan. 2025, doi: 10.48175/ijarsct-23112.

[15] C. Zhao and Y. Xun, "The analysis of dynamic evaluation of online shopping satisfaction based on the recurrent neural network model," *Scientific Reports*, vol. 15, no. 1, p. 21724, Jul. 2025, doi: 10.1038/s41598-025-06689-0.

[16] N. Akram, S. Victor, D. Raghava, M. V. Unni, P. Gottumukkala, and S. Garg, "Digital marketing strategy to increase sales conversion on e-commerce platforms based on LSTM-RNN model," in *Hybrid and Advanced Technologies*, London: CRC Press, 2025, pp. 358–363. doi: 10.1201/9781003559115-60.

[17] S. Shan, J. Sun, and R. M. C. Macawile, "Examining customer satisfaction through transformer-based sentiment analysis for improving bilingual e-commerce experiences," *IEEE Access*, vol. 13, pp. 51027–51041, 2025, doi: 10.1109/ACCESS.2025.3551666.

[18] F. Mancini, V. A. S. Precoma, L. A. De Oliveira, and F. Teixeira, "ClickstreamGPT: a transformer-based generative AI approach to clickstream prediction for E-commerce platforms," *Electronic Commerce Research*, pp. 1–25, Apr. 2026, doi: 10.1007/s10660-025-10071-7.

[19] C. Verma, P. Vijayalakshmi, N. Chaturvedi, U. Umesh, A. Rai, and A. Y. A. Bani Ahmad, "Artificial intelligence in marketing management: enhancing customer engagement and personalization," in *2025 International Conference on Pervasive Computational Technologies (ICPCT)*, IEEE, Feb. 2025, pp. 397–401. doi: 10.1109/ICPCT64145.2025.10940626.

[20] G. Mahalisa, S. Ratna, and M. Muflih, "Development of a collaborative recommendation system based on singular value decomposition (SVD) on e-commerce data," *Journal of Applied Informatics and Computing*, vol. 9, no. 6, pp. 3769–3773, Dec. 2025, doi: 10.30871/jaic.v9i6.11688.

[21] W. Silfianti, R. D. Syah, A. Suhendra, A. Isra, A. Darmayantie, and N. R. Ohorella, "A deep learning approach for tourism destination recommendation using IndoBERT and TF-IDF," *ILKOM Jurnal Ilmiah*, vol. 17, no. 3, pp. 241–251, Oct. 2025, doi: 10.33096/ilkom.v17i3.3069.241-251.

[22] Y. Mo and H. Wang, "Session-based recommendation method using popularity-stratified preference modeling," *Mathematics*, vol. 13, no. 6, p. 960, Mar. 2025, doi: 10.3390/math13060960.

[23] C. S. M. Ali and S. R. M. Zeebaree, "Personalization in digital marketing: leveraging machine learning for e-commerce," *Asian Journal of Research in Computer Science*, vol. 18, no. 3, pp. 105–129, Feb. 2025, doi: 10.9734/ajrcos/2025/v18i3582.
[24] A. Mustafa and N. Mazher, "Decoding Drop-Off Points : A multi-factor machine learning model for cart abandonment in," *ThinkTide Global Research Journal*, vol. 6, no. 3, pp. 9–26, 2025, [Online]. Available: https://thinktidejournal.com/index.php/TGRJ/article/view/5
[25] A. Syaifuddin, R. Saptono, A. Rohmadi, B. Widoyono, and B. Hendrasuryawan, "Optimizing e-commerce personalization through hybrid decision tree–nearest neighbor recommendation integration," *Jurnal Teknik Informatika (Jutif)*, vol. 7, no. 2, pp. 1028–1039, Apr. 2026, doi: 10.52436/1.jutif.2026.7.2.5418.

BIOGRAPHIES OF AUTHORS

Dr. Parashiva Murthy B. M. working as Assistant Professor in of Computer Science and Engineering, JSS Science and Technology University, Mysuru, Karnataka, has 12 years of academic service. He can be contacted at email: parashivamurthy@sjce.ac.in.

Dr. Scaria Alex working as Assistant Professor in Department of Information Technology, Amal Jyothi College of Engineering, Kottayam. He have +13 Years of teaching experience. He can be contacted at email: scariaalex@amaljyothi.ac.in.

Dr. Isaivani Mariyappan is currently working as an Assistant Professor in the Department of Electrical and Electronics Engineering, SRM Madurai College for Engineering and Technology, Sivaganga District, Tamil Nadu, India. She can be contacted at email: isainec06@gmail.com.

Dr. Kalyan Devappa Bamane academician and researcher with over 19 years of experience. He is currently an Associate Professor in the Department of Computer Engineering, Indira College of Engineering and Management, Parandwadi, Pune, Maharashtra, India. He can be contacted at email: kalyandbamane@gmail.com.

Dr. Kavitha R. with over 12 years of teaching experience in Computer Science and Engineering holds a Ph.D. from Manonmaniam Sundaranar University. She can be contacted at email: athikavi88@gmail.com.

Dr. S. Athinarayanan Associate Professor at Vel Tech, Chennai, has over 16 years of teaching experience, including 7 post-Ph.D. His expertise spans medical image processing, machine learning, blockchain, and system software. book. He can be contacted at email: aathithe@gmail.com.

Dr. Sunder R. Professor in School of computer science and engineering at Galgotias University, holds 20 years of teaching experience with Ph.D from Manonmaniam Sundaranar University. He can be contacted at email: sunder.r@galgotiasuniversity.edu.in.