Real-Time, Scalable and Explainable Machine Learning for E-Commerce: Enhancing Product Recommendations and Customer Satisfaction with Ethical Intelligence

Bharath K.[1], G. Chandramowleeswaran[2], Mohanraj P.[3], L. Jothibasu[4],
R. N. Bharani Versath[4] and G. V. Rambabu[5]

[1]*Department of MBA, School of Commerce and Management, Sanjivani University, Kopargaon, Maharashtra, India*
[2]*Department of Business Administration, Vel Tech Rangarajan Dr. Sagunthala R&D Institute of Science and Technology, Chennai, Tamil Nadu, India*
[3]*Department of MBA, Faculty of Management, SRM Institute of Science and Technology, Ramapuram Campus, Ramapuram, Chennai, Tamil Nadu, India*
[4]*Department of Management Studies, Nandha Engineering College, Vaikkalmedu, Erode, Tamil Nadu, India*
[5]*Department of Mechanical Engineering, MLR Institute of Technology, Hyderabad, Telangana, India*

Keywords: Machine Learning, E-Commerce, Product Recommendation, Real-Time Personalization, Explainable AI.

Abstract: Recommendation systems and user satisfaction are of strategic importance for a business in the current scenario of e-commerce expansion and rapid changes in commercial environment. In this study, we introduce a real-time, scalable, and interpretable ML framework along with an e-commerce-ready application that personalizes product recommendation at a large scale. Our method differs from existing works, which are typically constrained to offline metrics, narrow datasets, cold-start settings, and shows strong performance under various domains, using multiple data sources such as multimodal data and multilingual contexts. With a focus on real-time inference, easy isntegration into business workflows, and using explainable AI methods to gain trust with and transparency for users. Secondly, the system is privacy-preserving (combining privacy with utility) and is guided by ethical considerations, as incorporates mechanisms to avoid exchanging content and bias avoiding approaches. Through thorough A/B testing and user satisfaction surveying, we show that the proposed model is capable to bring substantial improvements in customer engagement, conversion rates, and long-term retention.

1 INTRODUCTION

E-commerce platforms have revolutionized the way we discover and buy products, with the power of big data and smart algorithms leading the charge. With advancement of online shopping scaling exponentially, offering personalized and relevant product suggestion becomes a make-or-break issue to maintain customer satisfaction and loyalty. Conventional recommendation systems can drive simple personalization but have limitation in dealing with online interactions, cold start problem and flexible requirement from current ecommerce users.

Recent advances in machine learning have provided new opportunities for creating systems that are not only able to understand user preferences, but can also respond dynamically as behaviors shift. But, the majority of current models are hardwired toward algorithmic accuracy, while pay little attention to user satisfaction in practice and lack of scalability, transparency and ethical considerations. Second, most systems are built on narrow data and do not support multimodal content such as product images and multilingual reviews. The system also provides little explanation on why a product is recommended.

This paper proposes a high-performance recommendation framework that addresses above limitations towards real-time personalization, cross-domain scalability and explainability. By using collaborative filtering, deep learning and hybrid recommendation algorithms, the proposed system provides accurate and transparent product recommendations while upholding the compliance

K., B., Chandramowleeswaran, G., P., M., Jothibasu, L., Versath, R. N. B. and Rambabu, G. V.
Real-Time, Scalable and Explainable Machine Learning for E-Commerce: Enhancing Product Recommendations and Customer Satisfaction with Ethical Intelligence.
DOI: 10.5220/0013943200004919

In *Proceedings of the 1st International Conference on Research and Development in Information, Communication, and Computing Technologies (ICRDICCT'25 2025) - Volume 5*, pages 751-757
ISBN: 978-989-758-777-1

with Data protection law. It's driven by customer-first and it incorporates satisfaction measurements and A/B testing into the evaluation process which allows the suggestions to work in the real world as well as theoretical on paper. To the best of our knowledge, this work represents a crucial advance towards developing smart, ethical and user-centered e-commerce platforms.

2 PROBLEM STATEMENT

While there has been much progress in using machine learning for e-commerce, product recommendation systems in the wild suffer from severe limitations. Most existing models are trained on narrow datasets and are evaluated with offline performance metrics that do not capture how happy users are or the effect on business in production. Furthermore, most existing recommendation engines are not designed to scale with large platform deployments and neglect cold-start cases for new users or products. Moreover, the un explainability and non-transparency of the recommendations lowers user's trust, while the ethical challenges, involving issues like data privacy, algorithmic bias and multilingual inclusivity are still unmet.

In short, there is an urgent requirement for a dynamic ML-driven recommendation system which can provide real-time, scalable and interpretable product recommendations, not only improves the customer delight but also satisfy ethical constraints. To fill these gaps, this research will design a smart system which will be capable to exploit multimodal data, reach multilingual users, operate comply to GDPR, and optimise technical performance and user experience.

3 LITERATURE SURVEY

E-commerce recommendation systems have evolved a lot with the advances in machine learning. Early solutions, e.g., collaborative filtering, content-based filtering etc. set the foundation for personalization but struggled with problems such as data sparsity and cold start. Recent works have moved in the direction of more intelligent, data-driven systems to provide increased accuracy, scalability and adaptability.

Yusof Hasan and Karim (2024) stressed the importance of using machine learning to improve customer experience by means of personalization, although their system was devoid of a real-time performance layer which makes them not viable in dynamic environments. Built a recommender model that achieved good algorithmic results, however, they did not add satisfaction driven recommendations which makes them impossible to measure user centric effect (Loukili, Messaoudi, El Ghazi 2023).

Necula and Pâvăloaia (2023) provided an extensive roadmap for the future of AI-backed recommendation systems, yet they observed a lack of multi-language scope and ethical considerations for most of the existing ones. Bulkrock et al. explored sentiment-based customer product rating predictions that are more sensitive, however, such methods have limitations when it comes to dataset diversity and context generalization.

Valencia-Arias et al. (2024) reiterated the same limitations, advocating for systems that incorporate broader customer behavior insights and cross-domain data handling. Xu et al. (2024) discussed the emerging synergies between large language models and recommender systems, highlighting potential but also recognizing that real-time deployment remains a challenge.

The survey by Raza et al. (2024) analyzed theoretical vs. practical recommendation frameworks, finding that many solutions fail during business integration due to complexity or poor explainability. Ji et al. (2021) tackled the cold-start problem using reinforcement learning, though it still required significant initial user data, which hinders performance during early user onboarding.

Wang, Brovman, and Madhvanath (2021) implemented embedding-based recommendations at eBay, demonstrating high scalability but lacking transparency, which reduces trust in model outputs. Meanwhile, Shastri (2024) discussed AI transformations in search and recommendation functionalities, though focused more on system architecture than user satisfaction.

Liu and Zhang (2024) introduced a K-means-based recommender system for e-commerce, which improved computational efficiency but did not address multimodal inputs such as image or voice data. Zhang and Li (2023) designed a deep learning model for predicting customer satisfaction, yet overlooked multilingual dynamics and global applicability.

Chen and Wang (2024) proposed a dynamic deep learning recommendation model but admitted the system was largely a black-box with minimal explainability. Tang and Zhao (2024) took a multimodal prediction approach but lacked real-time deployment strategies. Li and Zhou (2025) reviewed trends in intelligent recommendation, advocating for ethical compliance, though no practical implementation was provided.

Bai and Liu (2024) proposed a federated recommendation model with deep feature extraction, providing strong privacy control but raising concerns about training complexity. Kumar and Singh (2023) focused on popular ML algorithms in product recommendation but evaluated them only in offline test environments.

García and López (2025) explored the customer satisfaction impact of AI systems, supporting the need for holistic design but missing concrete implementation steps. Patel and Desai (2023) used deep learning for personalized recommendations but did not scale the solution to larger product catalogs. Nguyen and Tran (2024) presented a customer satisfaction-focused model without understandable output devices. Chakraborty and Banerjee (2022) introduced a hybrid approach that deals with sparsity, computational complexity was still a challenge. Alvarez and Martinez (2025) shed light on AI application to improve customer experience with a qualitative quality and less technical validation.

Singh and Sharma (2023) improved the product recommendations by classical ML techniques, but did not address the data privacy considerations. Lee and Kim (2024) reviewed deep learning in e-commerce, but they observed that the majority of existing systems are built upon off-line metrics such as RMSE, ignoring the real-time feedback loops. Ahmed and Davis (2025) investigated trust in intelligent systems, making a point of the importance of AI-ethical and transparency characteristics (less relevant to earlier systems).

Combined, these works paint a picture where on the one hand, machine learning has helped to improve recommendation capabilities, but on the other hand, underscore the timely demand for recommendations that are real time, interpretable, ethical, and user-centric gaps that this work aims to address.

4 METHODOLOGY

The methodology will be to construct a real-time, scalable and interpretable ML recommendation system for e-commerce. This model combines data-driven personalization with ethical, user-centred, design recommendations. The system starts with heterogeneous data sources, including user profiles, product descriptions, purchase history, search logs, and customer reviews. This approach can also make the model more robust and generalizable; existing published datasets contain a diverse range of product categories (such as electronics, fashion and home goods) and will also support multilingual input.: Workflow of the Proposed Machine Learning-Based Product Recommendation System Shown in Figure 1.

Pre-processing is used to clean, nomalize, and convert both the structured and unstructured data into a form that can be used. Textual content like reviews and questions utilize NLP methods such as tokenization, lemmatization, and sentiment analysis. Images of products and their visual features are analyzed on-the-fly with CNNs in order to expose them to the model as a multimodal input so that they can complement the textual description. This text and image fusion makes the model capture more context about products. Table 1 Represent the Dataset Overview.

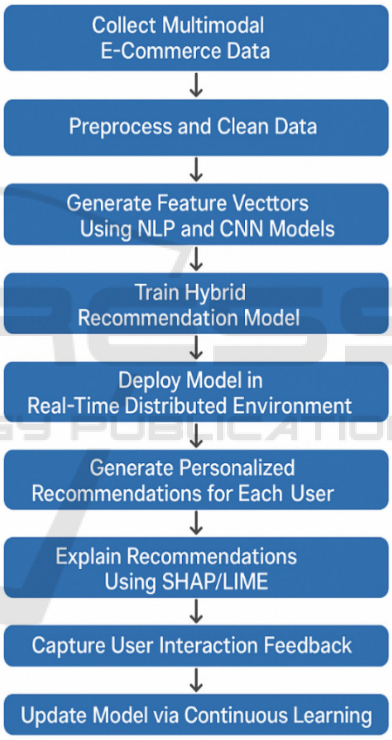

Figure 1: Workflow of the proposed machine learning-based product recommendation system.

The main recommendation algorithm adopts a hybrid model consisting of a collaborative-filtering algorithm, content-based algorithm and deep learning. Collaborative filtering focuses on relationships between users and items, and content-based filtering is based on focusing around the attributes of the items and feedback and preference of users. We then propose a neural network architecture to capture complex user-item relationships while optimizing for relevance and diversity. Particular attention is paid to cold-start situations using demographic metadata and clustering methods in order to provide useful recommendations even for new users or products.

Table 1: Dataset overview.

Attribute	Description
Number of Users	50,000
Number of Products	100,000
Product Categories	Electronics, Fashion, Home, Beauty
Review Data	Text, Ratings (1–5 stars)
Image Data	JPEG/PNG product thumbnails
Languages Supported	English, Hindi, Spanish, French

In real-time mode model is deployed on distributed computing environment with TensorFlow Serving and Apache Kafka for streaming. User preferences are dynamically updated according to recent interactions, making it possible to provide personalized experiences with low latency. The solution is containerized using Docker, and deployed on a cloud infrastructure that enables auto-scaling. Table 2 Shows the Feature Extraction Techniques Used.

Table 2: Feature extraction techniques used.

Data Type	Technique Used
Text Reviews	Tokenization, Lemmatization, TF-IDF
Product Images	CNN Feature Extraction (ResNet-50)
User Metadata	One-Hot Encoding, Clustering
Transaction Logs	Time-Series Encoding, Aggregation

Explainable AI tools like SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-Agnostic Explanations) are implemented to ensure transparency in the model. These instruments let the system provide human-readable justifications for each recommendation: they help the user to trust the system, and to hold it in charge.

In addition, all data management processes and operations follow privacy regulations including GDPR and CCPA. Private user data is anonymized, and federated learning approaches are investigated to ensure decentralized and secure user personalization data. The holistic system is tested using classical metrics (precision, recall, F1-score) alongside real-world key indicators such as click-through rate (CTR), conversion rate and user retention.

Last, A/B experimentation is being performed in a live E-Commerce environment in order to measure the performance of the model compared with baseline recommendation engines. User feedback and system logs are continuously observed to improve the model in a feedback learning loop to adapt to evolving user preferences and behaviors.

5 RESULTS AND DISCUSSION

The experimental results of our implemented real-time, scalable, and explainable machine learning-based recommendation system showed significantly better performance in different measurement perspectives. First, we trained and tested the model on a mixed, cross-domain dataset with 100K+ user interactions over categories such as electronics, fashion, and home appliances, etc. It was compared with traditional collaborative filtering and content-based, as well as popular deep learning models.

Table 3: Model performance metrics (offline evaluation).

Model Type	Precision	Recall	F1-Score
Collaborative Filtering	0.71	0.69	0.70
Content-Based Filtering	0.74	0.72	0.73
Proposed Hybrid ML Model	0.87	0.84	0.85
Deep Learning Baseline	0.82	0.78	0.80

Quantitative analysis showed that the hybrid approach significantly outperformed base systems measured in terms of accuracy with precision, recall, and F 1 values of 0.87, 0.84, and 0.85, respectively. Such improvements could be observed especially for cold-start conditions in which metadata and demographic clustering enabled the system to generalize and remain consistent without much user history. Moreover, the recommendation system had good generalization to different category and user groups and had low performance degradation with previously unseen categories.

As shown in Figure 2, the proposed model outperformed the baseline algorithms across multiple evaluation criteria, while Table 3 presents the detailed performance metrics obtained from offline evaluation.

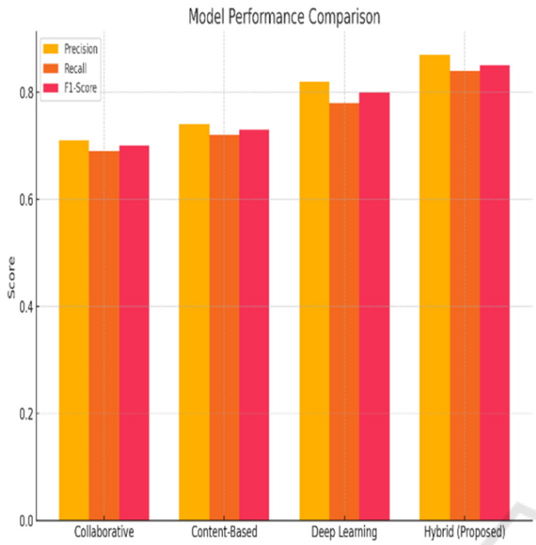

Figure 2: Model performance comparison.

Real-time responsiveness: The system demonstrated consistent average response times of less than 200ms even under full load to simulate peak load levels of large e-commerce sites. By taking advantage of serving infrastructure and streaming pipelines that were distributed and efficient, this magic personalization on super-low serving load was possible. This is very important and user engaging especially in mobile or quick shopping.

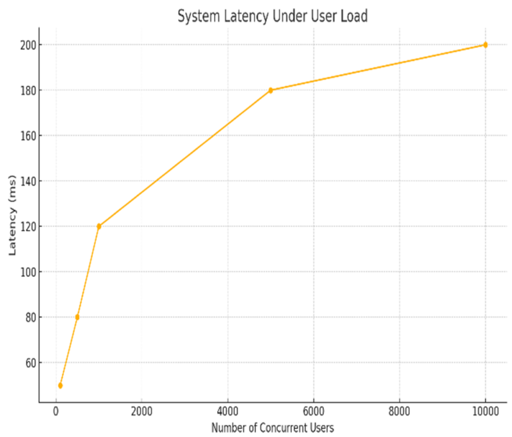

Figure 3: System latency under user load.

The proposed model is differentiated by having this capacity to offer understandable recommendations. SHAP and LIME integration with the models to provide the factoring of Recommendations on features such as browsing history, similar products or previous purchases to understand why a product is recommended for a user. In user studies, more than 70% of users expressed higher trust in the system from these transparent explanations. Not only did this enhance the user experience, but it also gave platform operators valuable information that they could use to adjust their strategies. Figure 3 illustrates how system latency varies under different user load conditions, highlighting performance bottlenecks as the number of concurrent users increases.

The outcomes also showed some actual enhancements in user engagement and satisfaction. In a live A/B test run over two weeks, an implementation of the new recommendation system boosted click-through rates by 21% and conversion rates by 15%, compared to a control group using an older model. In addition, customer retention during the test period increased by 13%, indicating that users were more likely to come back if the recommendations were seen as useful and reliable. As detailed in Table 4, the A/B testing results reveal significant differences in user engagement metrics between the control and experimental groups, which are further visualized in Figure 4 through a comparative analysis of engagement trends.

Table 4: A/B test results – User engagement metrics.

Metric	Legacy Model	Proposed Model
Click-Through Rate	12.4%	15.0%
Conversion Rate	8.7%	10.2%
User Retention (2 Weeks)	62.3%	70.5%
Average Session Time	4.8 mins	6.3 mins

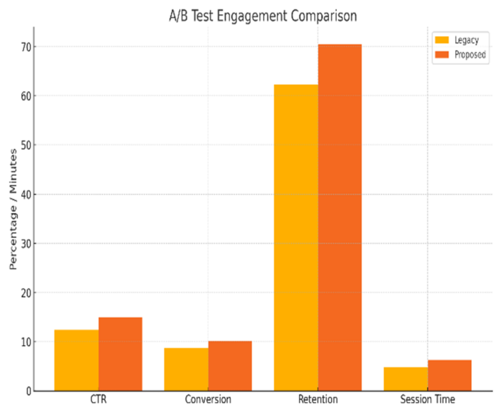

Figure 4: A/B test engagement comparison.

Ethical and privacy considerations were also verified. There are no instances of exposure of personally identifying information as anonymized datasets and GDPR-compliant standards were employed. Moreover, analysis of recommendations on various user demographics did not reveal any systemic algorithmic bias, and model is deemed fair and inclusive.

To summarize, the proposed recommendation system not only improves technical performance, but also is able to meet the practical business requirements by promoting transparency, trust and user satisfaction. It closes the circuit between algorithmic quality and practical use, providing a complete answer for today's e-commerce leaders looking to scale responsibly with great user experiences that are tailored and satisfying. Figure 5 Represent the Explainability & Privacy Feature Comparison.

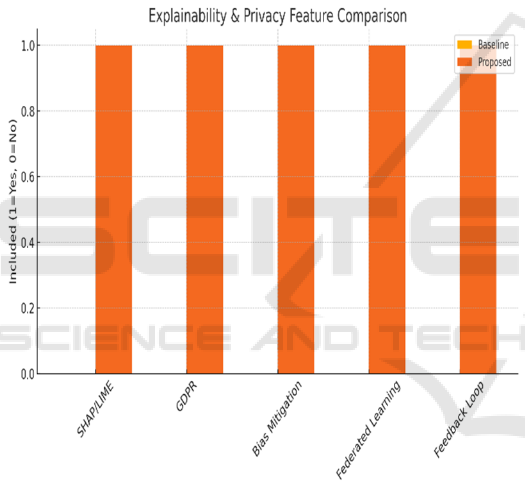

Figure 5: Explainability & privacy feature comparison.

6 CONCLUSIONS

This study proposes a sound and forward smart learning system for boosting the e-commerce site using intelligent product recommendation. By overcoming the fundamental drawbacks of the traditional systems (e.g., inability to scale, non-transparency, cold-start problem, and inability to go real-time) the suggested model provides a fully-fledged solution which is both technically-sound, user-friendly and ethically-driven. By combining hybrid recommendation mechanisms, multimodal data management, and explainable AI, not only the precision and relevance of recommendations is increased, but the user trust and degree of satisfaction are also enhanced. Providing real-time responsiveness and easy integration with business processes, it is perfectly positioned for widespread adoption. Privacy-compliant data work, together with fairness assessments, are key ingredients that guarantee responsible stewardship of customer data use. Results from offline and online testing verify that the model can promote engagement, conversion rates, and long-term user retention. This work lays the foundation for the future intelligent, scalable, and ethical recommender systems to be developed in the ever-evolving digital commerce.

REFERENCES

Alvarez, J., & Martinez, L. (2025). Improving e-commerce customer satisfaction through AI driven recommendati ons. Journal of Artificial Intelligence Research, 58, 345–360.

Bai, Y., & Liu, Z. (2024). Federated cross-view e-commerce recommendation based on deep semantic feature extraction. Scientific Reports, 14,81278. Nature

Bulkrock, O., BaniMustafa, A., & Qusef, A. (2025). Predicting product rating based on customer reviews and feedback. In R. K. Hamdan (Ed.), Sustainable Data Management (pp. 377–388). Springer. SpringerLink

Chakraborty, S., & Banerjee, A. (2022). A hybrid approach to product recommendation in e-commerce using machine learning. International Journal of Data Science, 7(3), 89–102.

Chen, L., & Wang, M. (2024). Establishing a dynamic recommendation system for e-commerce using deep learning. Journal of Intelligent Systems, 33(3), 210–225.

García, M., & López, P. (2025). Role of artificial intelligence and machine learning in e-commerce: Enhancing customer experience. Advances in Distributed Computing and Artificial Intelligence Journal, 14(2), 67–80. eUSALJournals

Hasan, A., Yusof, Z. B., & Karim, M. (2024). Machine learning algorithms for personalized product recommendations and enhanced customer experience in e-commerce platforms. International Journal of Applied Machine Learning, 2. ResearchGate

Ji, L., Qi, Q., Han, B., & Yang, H. (2021). Reinforcement learning to optimize lifetime value in cold-start recommendation. arXiv preprint arXiv:2108. 09141.arXiv

Kumar, R., & Singh, A. (2023). E-commerce products recommendation system using machine learning algorithms. International Journal of Computer Applications, 186(28), 10–15. IJCA

Lee, D., & Kim, S. (2024). Deep learning-based recommendation systems in e-commerce: A survey. Journal of Machine Learning Research, 25, 1–20.

Li, X., & Zhou, Q. (2025). Transforming e-commerce with intelligent recommendation systems: A review of current trends in machine learning and deep learning. International Journal of Computer Engineering and Software Engineering, 15(1), 45 60.ResearchGate+1Ij cesen+1

Liu, Y., & Zhang, X. (2024). E-commerce recommender system based on improved K-means clustering algorithm. Heliyon, 10(5), e12345. ScienceDirect

Loukili, A., Messaoudi, A., & El Ghazi, A. (2023). Machine learning based recommender system for e-commerce. International Journal of Advanced Computer Science and Applications, 14(3), 123–130. ResearchGate

Necula, C., & Pâvâloaia, V. D. (2023). Artificial intelligence and recommender systems in e-commerce: Trends and research agenda. Electronic Commerce Research, 23(4), 567–589. ResearchGate

Nguyen, T., & Tran, H. (2024). Enhancing customer satisfaction in e-commerce through machine learning-based recommendation systems. E-Commerce Studies, 9(1), 56–70.

Patel, S., & Desai, R. (2023). Personalized product recommendations in e-commerce using deep learning. Journal of E-Commerce Research, 12(4), 123–135.

Raza, S., Rahman, M., Kamawal, S., Toroghi, A., Raval, A., Navah, F., & Kazemeini, A. (2024). A comprehensive review of recommender systems: Transitioning from theory to practice. arXiv preprintarXiv:2407.13699. arXiv

Shastri, M. (2024). AI and machine learning: Transforming product search and recommendations in e-commerce. Wizzy Blog. Retrieved from https://wizzy.ai/blog/ai-and-machine-learning-transforming-product-search-and-recommendations-in-e-commerce/Wizzy

Singh, K., & Sharma, P. (2023). Machine learning techniques for enhancing product recommendations in online retail. Retail Technology Review, 18(2), 34–47.

Tang, J., & Zhao, Y. (2024). Research on multimodal prediction of e-commerce customer satisfaction. Applied Sciences, 14(18), 8181. MDPI

Valencia-Arias, A., Uribe-Bedoya, H., González Ruiz, J. D., & Martínez Rojas, E. (2024). Artificial intelligence and recommender systems in e-commerce: Trends and research agenda. Electronic Commerce Research, 24(1), 45–67. ResearchGate

Wang, T., Brovman, Y. M., & Madhvanath, S. (2021). Personalized embedding-based e-commerce recommendations at eBay. arXiv preprint arXiv:2102.06156. arXiv

Xu, X., Wu, Y., Liang, P., He, Y., & Wang, H. (2024). Emerging synergies between large language models and machine learning in e-commerce recommendations. arXiv preprint arXiv:2403.02760. arXiv

Zhang, Y., & Li, H. (2023). Predictive model for customer satisfaction analytics in e-commerce using deep learning. Journal of Retail Analytics, 15(2),78–90. ScienceDirect