2024 4th International Conference on Mobile Networks and Wireless Communications (ICMNWC) | 979-8-3315-2834-8/24/$31.00 ©2024 IEEE | DOI: 10.1109/ICMNWC63764.2024.10872138

A Systematic Study of Machine Learning Applications in E-Commerce UX Personalization

1st M.K.C.P. Nishamali
Sri Lanka Institute of Information Technology
Malabe, Sri Lanka
ms23018778@my.sliit.lk

2nd Gihan Saminda Pathirage
Sri Lanka Institute of Information Technology
Malabe, Sri Lanka
ms23003378@my.sliit.lk

3rd Samitha Herath
Sri Lanka Institute of Information Technology
Malabe, Sri Lanka
ms23016934@my.sliit.lk

4th Penusha Herath
Sri Lanka Institute of Information Technology
Malabe, Sri Lanka
ms23008878@my.sliit.lk

5th Jagath Wickramarathne
Faculty of Computing
Sri Lanka Institute of Information Technology
Malabe, Sri Lanka
jagath.w@sliit.lk

***Abstract*—This study provides a systematic analysis of the role of machine learning in personalizing e-commerce user experiences (UX). Through a review of selected recent literature, the study explores various machine learning techniques applied to e-commerce, including supervised learning, unsupervised learning, deep learning, and ensemble methods. The research discusses these approaches' effectiveness in enhancing UX through personalized recommendations, search results, dynamic pricing models, and virtual try-on experiences. The analysis examines four main areas: recommendation systems for improved product discovery and user engagement, dynamic pricing optimization for maximizing revenue and customer satisfaction, virtual try-on technologies for enhancing fashion retail experiences, and personalized search. The study investigates how these technologies contribute to creating engaging and efficient shopping experiences while examining implementation challenges such as data privacy and algorithmic bias. Additionally, the research discusses emerging trends, technological advancements, and future research directions to further advance personalization in e-commerce. Overall, this research contributes to the understanding of machine learning in e-commerce personalization for both researchers and practitioners.**

***Index Terms*—e-commerce ux personalization, machine learning in e-commerce, personalized recommendations, personalized search, virtual try-on technologies**

I. Introduction

The rapid growth of e-commerce has transformed the retail landscape, offering unprecedented convenience and choice to consumers worldwide. As online marketplaces become increasingly competitive, personalization has emerged as a key differentiator in enhancing user experience (UX) and driving customer loyalty. Machine learning (ML) technologies have played a pivotal role in this transformation, enabling e-commerce platforms to tailor their offerings to individual user preferences and behaviors.

Personalization in e-commerce encompasses a wide range of applications, from product recommendations and dynamic pricing to virtual try-on experiences and customized search results. By leveraging vast amounts of user data and advanced algorithms, machine learning models can predict user preferences, optimize pricing strategies, and create immersive shopping experiences that closely mimic in-store interactions.

However, the implementation of ML-driven personalization in e-commerce is not without challenges. Issues related to data privacy, algorithmic bias, and the need for transparent and explainable AI systems pose significant hurdles. Moreover, as consumer expectations continue to evolve, e-commerce platforms must continually innovate to provide increasingly sophisticated and seamless personalized experiences.

The main goal of this systematic review was to explore the current state of machine learning applications in personalizing e-commerce user experiences, identify key challenges, and highlight promising future directions. Specifically, this study addressed the following research questions:

1) What are the current prominent methods of personalizing e-commerce user experiences using machine learning?
2) What challenges do these personalization methods face in their implementation and effectiveness?
3) What are the future directions that researchers and practitioners should focus on to advance e-commerce personalization?

By addressing these questions, this review aims to provide comprehensive insights into how ML can create more engaging, efficient, and user-centric online shopping experiences.

II. Literature Review Methodology

An overview of the process followed when compiling this paper is shown in Fig. 1.

A. Search Strategy

A systematic search of IEEE Xplore and Elsevier was conducted to find relevant studies using combinations of

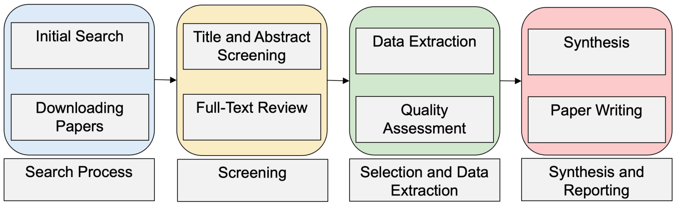

Fig. 1. Review Process Methodology

keywords related to e-commerce, machine learning, and associated technologies. The search terms included: e-commerce AND personalization; e-commerce AND machine learning; natural language processing AND e-commerce; product recommendation AND e-commerce; product pricing AND e-commerce; collaborative filtering AND e-commerce; chatbot AND e-commerce; predictive analytics AND e-commerce; virtual try-on AND e-commerce; search optimization AND e-commerce; and customer segmentation AND e-commerce.

B. Inclusion and Exclusion Criteria

Studies were included if they met the following criteria:

1) They focus on personalizing e-commerce user experience using machine learning techniques.
2) They present empirical evaluations or implementations of machine learning models for personalization.
3) They are published in reputable peer-reviewed journals or conferences.
4) They are written in English and published between 2020 and 2024.

Studies that did not meet these criteria, such as those focusing on non-machine learning approaches or non-e-commerce contexts, were excluded.

C. Data Extraction

The following data were extracted from the selected studies:

1) The specific machine learning techniques employed for personalization.
2) The types of e-commerce UX elements being personalized (e.g., product recommendations, search results).
3) The features utilized for personalization.
4) The datasets used for training and evaluation (if available).
5) The evaluation metrics reported (e.g., click-through rates, conversion rates).
6) The key findings and conclusions of each study.

The extracted data was analyzed to summarize research trends and challenges in ML-driven e-commerce UX personalization.

III. Results and Discussion

After analyzing the selected literature, the enhancement of e-commerce UX based on machine learning approaches was categorized into four main categories: Personalized Product Recommendations, Dynamic Pricing Models, Virtual Try-On, and Personalized E-commerce Search. Key takeaways from each selected paper were shown in Table II. Through this analysis, prominent ML methods used in each category were identified, as shown in Table I and Fig. 2. Papers that didn't fit directly into these main categories were listed under 'Other' to ensure comprehensive coverage of the field.

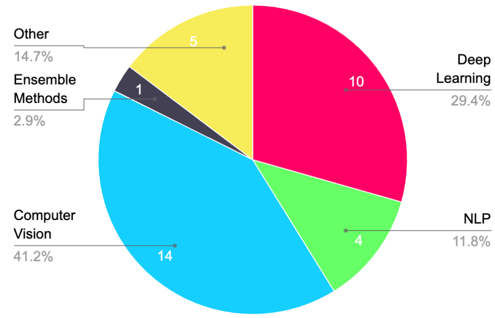

Fig. 2. Key Machine Learning Approaches in Literature

TABLE I
Categorization of Papers by ML Methods

Category	Papers
Deep Learning	[1], [2], [3], [4], [5], [6], [7], [8], [9], [10]
NLP	[11], [12], [13], [14]
Computer Vision	[11], [15], [16], [2], [17], [18], [3], [4], [5], [19], [6], [7], [20], [8]
Ensemble Methods	[21]
Other	[22], [23], [24], [25], [26]

A. Personalized Product Recommendations

Personalized product recommendations have become crucial in e-commerce, improving user experience and boosting sales. These recommendations leverage advanced algorithms and deep neural networks to analyze customer data, delivering targeted suggestions based on individual browsing history and product preferences. The impact of personalized recommendations is substantial. Research indicates that when customers receive personalized suggestions, the average order value can increase by up to 369% [9]. This dramatic improvement in conversion rates underscores the effectiveness of well-implemented recommendation systems.

However, the implementation of these systems is not without challenges. Ethical concerns related to data privacy and potential algorithmic bias must be carefully addressed to maintain consumer trust [10]. Striking the right balance between personalization and privacy is crucial for long-term success.

Various machine learning methods have proven effective for generating personalized recommendations. LightGBM, for instance, has shown superior performance compared to deep neural networks in metrics such as mean average precision and recall [26]. Long Short-Term Memory (LSTM) architectures, when combined with attention mechanisms, excel at capturing temporal patterns in user interactions, further improving recommendation accuracy [10].

Innovative approaches continue to emerge in this field. Recent research in e-commerce recommendations [8] has

TABLE II
SUMMARIZATION OF SELECTED PAPERS

Category	Authors	Key Contribution	Main Findings/Implications
Personalized Product Recommendations	Zhong & Wang (2021) [8]	Product recommendation method using image and review scores.	Outperforms existing image-based recommendations; enhances user satisfaction.
	Zhang et al. (2024) [1]	ART com-rec for composite artwork recommendations.	Improves recommendation accuracy using keyword-driven correlation graph search.
	Nguyen et al. (2024) [26]	LightGBM-based personalized product recommendation model.	Outperforms Deep Neural Network; addresses cold-start problems.
	Pande et al. (2023) [9]	GAP model for personalized recommendations.	Achieves real-time recommendations with low latency (50ms); increases revenue by 3x.
	Qu (2024) [23]	Vegetable replenishment and pricing strategies.	Uses time series and multi-objective planning; optimizes stocking and pricing.
	G et al. (2024) [10]	Personalized e-commerce using machine learning.	LSTM with attention mechanism improves recommendation accuracy.
Dynamic Pricing Models	El Youbi et al. (2023) [21]	Machine learning-driven dynamic pricing strategies.	Gradient Boosting Machines achieve high accuracy (R2 = 0.92) in price prediction.
	Sudharson et al. (2023) [24]	AI-powered shopbot for price comparison.	Tracks and compares product prices across e-commerce platforms.
Personalized Search Results	Li et al. (2023) [4]	DATE framework for product retrieval and grounding.	Outperforms weakly-supervised and fully-supervised methods in product search.
	Bansal et al. (2021) [7]	Framework for image-based search in e-commerce.	Reviews various CBIR algorithms; proposes Flutter framework for hybrid apps.
	Ma'Rufah et al. (2023) [3]	Visual search system using Siamese Neural Network.	Achieves up to 97% accuracy in image similarity predictions.
	Afifah & Wang (2023) [20]	VSS effectiveness measurement using Delphi Method.	Proposes a construct for measuring visual search service effectiveness.
Real-Time Chatbots and Virtual Assistants	Sharmila et al. (2024) [11]	Domain-specific chatbot for e-commerce.	Integrates image recognition for product search and recommendations.
	Keerthi Kumar et al. (2024) [14]	Hebron chatbot for e-commerce customer support.	Utilizes ML for natural language understanding; enhances customer service efficiency.
	Licapa-Rodriguez et al. (2021) [13]	EcoBot: Virtual assistant for ecological product e-commerce.	Increased transactions by 14% and improved user experience.
	Gupta et al. (2024) [25]	AI application in e-commerce.	Chatbots and virtual assistants enhance customer interactions and personalization.
	Olujimi & Ade-Ibijola (2023) [12]	NLP techniques for automating customer inquiries.	Reviews NLP applications in customer service; identifies challenges and opportunities.
Virtual Try-On	Shams et al. (2024) [15]	5GARderobe: Scalable real-time virtual wardrobe.	Implements MR solutions for virtual try-ons; reduces size-related returns.
	Namboodiri et al. (2021) [17]	GAN-based try-on system improving CA-GAN.	Enhances photorealistic virtual try-on with improved U-Net generator.
	Li et al. (2023) [5]	POVNet for image-based virtual try-on.	Preserves garment properties and textures; supports mixing various garment types.
	Nguyen-Ngoc et al. (2023) [2]	DM-VTON: Distilled Mobile Real-Time Virtual Try-On.	Achieves 40 fps on Nvidia Tesla T4 GPU; reduces runtime and memory usage.
	Majithia et al. (2022) [18]	3D garment digitization from monocular 2D images.	Generalizes well on real-world fashion catalog images; uses fixed topology parametric templates.
	Kishore Kumar Rejeti et al. (2023) [19]	Virtual fit using computer vision and Trimesh.	Allows try-on of outfits from any website without large product image database.
	Fele et al. (2022) [6]	C-VTON: Context-Driven Image-Based Virtual Try-On.	Outperforms state-of-the-art methods on VITON and MPV datasets.
	Rochana & Juliet (2024) [22]	Virtual dress trials leveraging GANs.	Enhances online shopping with size recommendations and chat support.
Surveys	Gupta et al. (2024) [25]	AI application in e-commerce.	Comprehensive review of AI transforming various aspects of e-commerce.

explored combining visual search with review sentiment analysis, offering a more nuanced approach to personalization. Complementing these efforts, graph neural networks and reinforcement learning techniques are being explored to refine the personalization process [9]. These advanced methods promise to drive even greater user engagement and sales, potentially enhancing key metrics like Average Order Value and conversion rates [10], [9], [26].

The development of sophisticated models like the Guest's Attribute Preferences (GAP) model has shown significant promise. By scoring guest preferences based on product attributes, this approach has led to notable improvements in user engagement and revenue. Future enhancements to this model could involve real-time data analysis and the use of microservices frameworks [9].

As the field evolves, researchers face the "paradox of personalization," balancing tailored experiences with privacy concerns. Personalization can enhance brand loyalty but may also trigger negative consumer reactions. Future research should leverage sophisticated algorithms and ethical considerations to develop recommendation systems that truly resonate with users [9].

B. Dynamic Pricing Models

Another key aspect of e-commerce personalization is dynamic pricing, which leverages real-time adjustments to optimize revenue and enhance customer satisfaction. These models leverage historical transaction data and customer behavior to create personalized pricing strategies that align with individual preferences and foster loyalty [21], [10].

Machine learning techniques, particularly Gradient Boosting Machines (GBM), have proven highly effective in this domain. GBMs excel at capturing complex relationships within data, delivering accurate pricing predictions with low Mean Squared Error (MSE) and high R-squared scores on validation sets [21]. This precision enables e-commerce platforms to implement responsive pricing strategies that can adapt quickly to the dynamic online marketplace.

Other prominent machine learning methods in dynamic pricing include Random Forest (RF) and Neural Networks (NN). These algorithms shine in their ability to handle large datasets and adapt in real-time. Long Short-Term Memory (LSTM) models have also found application in this field, contributing to both personalized recommendations and pricing strategies by capturing temporal patterns in user interactions [23], [10].

The strength of these advanced techniques lies in their capacity to model complex pricing dynamics and reveal non-linear relationships in customer behavior and price elasticity [21]. However, implementing dynamic pricing models is not without challenges. Issues such as data processing complexity, potential biases in model outputs, and synchronization problems during peak periods persist [23].

Looking ahead, future research in dynamic pricing models could benefit from exploring advanced machine learning techniques such as deep learning and refined LSTM networks. These approaches could potentially improve pricing personalization, offer better interpretation of user interactions, and enhance customer segmentation.

Addressing current limitations, such as the fixed treatment of cost-plus rates and data processing complexity, could lead to more accurate and adaptable pricing strategies that respond dynamically to market conditions [23], [21]. As the field evolves, researchers must adapt to changing market conditions and customer behaviors. By focusing on these areas, researchers can develop more effective and responsive dynamic pricing frameworks that not only enhance revenue but also improve customer satisfaction, paving the way for the next generation of e-commerce pricing strategies.

C. Real-Time Chatbots and Virtual Assistants

Complementing pricing strategies, chatbots and virtual assistants emerge as another key advancement, enhancing customer interactions and streamlining purchasing. By leveraging natural language processing (NLP), these systems facilitate seamless dialogue between consumers and machines, enhancing trust, communication, and overall user satisfaction during online shopping experiences [13]. The impact of chatbots in e-commerce is multifaceted. They provide immediate assistance and personalized recommendations, help users navigate product offerings, compare prices, and make informed decisions. This enhanced user experience has led to increased sales and improved customer retention rates [25], [12], [14], [24]. Moreover, by automating routine customer service tasks, chatbots enable human employees to focus on more complex issues, thereby optimizing operational efficiency [12].

Machine learning methods, particularly deep learning architectures employing reinforcement learning, have significantly enhanced chatbot effectiveness. These advanced algorithms excel at processing user input and generating appropriate responses [11]. NLP techniques play a crucial role in understanding user queries and providing relevant answers [12]. Some chatbots even incorporate image recognition algorithms like VGG.net, enabling real-time product recommendations based on user-uploaded images [11].

The application of chatbots extends beyond e-commerce. In education, they assess students' skills, provide tailored feedback, and assist with administrative tasks [11]. In customer service across various sectors, these technologies offer 24/7 support, address basic queries, and enhance user satisfaction through personalized interactions [25], [13].

Despite their benefits, implementing chatbots comes with challenges. Data ambiguity, arising from the complexities of human language, can lead to misunderstandings and inaccurate responses [25]. Many users perceive chatbots as lacking empathy, often preferring human interaction. Additionally, the initial investment in AI implementation may not yield desired outcomes if the technology fails to meet customer expectations, potentially damaging brand image and customer satisfaction.

Future research in chatbot technology should enhance NLP for better responsiveness and accuracy. Advanced deep learning and reinforcement learning can improve user input processing, while word sense disambiguation can reduce misunderstandings. Integrating image recognition for product recommendations can create a more interactive shopping experience. These advancements will lead to more efficient and user-friendly chatbots, enhancing e-commerce.

D. Virtual Try-On

Virtual Try-On (VTON) technology, complementing earlier personalization techniques, transforms fashion e-commerce by leveraging machine learning and GANs. These systems enable customers to virtually try on clothing, creating immersive shopping experiences that merge digital and physical retail interactions. VTON technology addresses the common issue of clothes looking perfect on models but not fitting the average buyer [19].

GAN-based architectures, such as the Context-Driven Virtual Try-On Network (C-VTON), employ a sophisticated two-stage pipeline. This approach combines geometric matching and context-aware image generation to produce photo-realistic virtual try-on images [6]. Recent advances in GAN frameworks, including optimized U-Net generators and refined training processes, have further improved image quality and efficiency [17].

One notable study within the domain of real-time virtual try-on systems is the development of the Distilled Mobile Real-time Virtual Try-On (DM-VTON) system. This approach exemplifies progress in prioritizing runtime efficiency while maintaining output quality, highlighting the potential of machine learning in enhancing virtual try-on capabilities [2].

Despite these technological advancements, current VTON systems exhibit both strengths and limitations. While GANs excel at generating photorealistic images that enhance the online shopping experience [17], [18], 2D image-based solutions often struggle with accurately representing garment fit and high-frequency texture details [22], [18]. Challenges persist when dealing with diverse poses and self-occlusions, limiting their applicability to standard body shapes and poses [6], [18].

Recent studies have focused on enhancing Virtual Try-On (VTON) technologies. Techniques like VITON use geometric matching and image synthesis to improve clothing transfer realism [6]. Integrating GANs and Conditional GANs (CGANs) can generate diverse clothing designs and enhance user experiences through augmented reality. Multi-garment try-on systems, such as POVNet, address layering complexities but still struggle with texture detail [5].

Future research in VTON systems should enhance garment simulation and expand clothing styles for realism [15]. Advanced interactions like gesture and voice controls can improve user experience, while accommodating diverse body types promotes inclusivity. Using enhanced GAN architectures can yield more photorealistic outputs and better fit representations [22], [17]. These advancements will improve Virtual Try-On systems and bridge digital and physical shopping.

E. Personalized E-commerce Search

Personalized e-commerce search has become crucial for improving user experience by streamlining product discovery and search relevance. Fashion e-retail platforms face growing search complexity as the user base increases and individuals find it difficult to translate visual preferences into searchable terms [3], which has prompted researchers to explore innovative search methodologies.

A notable advancement in this field is the rise of visual search technologies. These systems enable users to find products based on images rather than text, providing a significant advantage for those who struggle to express their needs verbally [20]. This approach is particularly beneficial in fashion and home decor e-commerce, where visual attributes play a crucial role in purchasing decisions.

Advanced recommendation systems that consider user preferences and keyword correlations have also made significant strides. These systems present curated product suggestions, minimizing irrelevant options and improving overall user satisfaction [1], [7]. By understanding individual user behavior and preferences, these systems can provide a more tailored shopping experience.

Machine learning methods play a pivotal role in optimizing personalized e-commerce search. Techniques like Siamese Neural Networks and Multi-Scale Convolutional Neural Networks (CNNs) enhance feature extraction, improving visual search capabilities in fashion e-retail contexts. Transformer-based models such as BERT are applied to text data, integrating textual descriptions with image features for more accurate product matching [16].

Research in this field has explored various approaches to enhance user experience and improve search accuracy. One such method is content-based product image retrieval, which leverages deep learning and CNNs to help users find products more accurately based on visual content. Additionally, composite recommendations suggest artworks based on user-defined keywords, catering to complex preferences [1]. Furthermore, a transformer-based multimodal framework has been proposed to improve product retrieval and grounding by combining textual and visual data, while also addressing domain adaptation for unannotated data [4].

Despite advancements, implementing personalized e-commerce search faces challenges. Traditional content-based search engines rely on basic image attributes and fail to capture nuanced preferences. The rapid growth of e-commerce generates large datasets, complicating effective search functionalities and accurate product retrieval, particularly with cross-modal grounding.

Future research in personalized e-commerce search could focus on advancing visual search technologies and multimodal similarity methods. Utilizing Siamese Neural Networks with Multi-Scale CNNs may enhance feature extraction precision in fashion e-retail [3]. Additionally, developing sophisticated transformer-based multimodal similarity searches could improve understanding of user preferences for more tailored results. Integrating composite recommendation systems that use user keywords and product correlations can lead to a reduction in decision fatigue and an enhanced user experience.

IV. Conclusion

This systematic review highlighted machine learning's significant impact on personalizing e-commerce experiences. ML algorithms enhanced customer satisfaction and increased sales through product recommendations, dynamic pricing, virtual try-ons, and personalized search. Advanced technologies like GANs, NLP, and computer vision led to more intuitive and engaging online shopping experiences.

However, challenges persisted in data privacy, algorithmic bias, and inclusivity. Future research should focus on developing more sophisticated, ethical, and user-centric ML models that adapt to diverse customer needs. Addressing these challenges and leveraging emerging technologies will allow the e-commerce industry to create more personalized, accessible experiences, driving innovation and growth in the digital marketplace.

References

[1] J. Zhang, W. Zhu, B. J. Ahn, and Y. Zhou, "Composite recommendation of artworks in e-commerce based on user keyword-driven correlation graph search," *Tsinghua Sci. Technol.*, vol. 29, no. 1, pp. 174–184, Feb 2024.

[2] K.-N. Nguyen-Ngoc, T.-T. Phan-Nguyen, K.-D. Le, T. V. Nguyen, M.-T. Tran, and T.-N. Le, "Dm-vton: Distilled mobile real-time virtual try-on," in *2023 IEEE International Symposium on Mixed and Augmented Reality Adjunct (ISMAR-Adjunct)*. Sydney, Australia: IEEE, Oct 2023, pp. 695–700.

[3] L. Ma'Rufah, T. Karlita, U. Sa'Adah, and W. A. Fauzi, "A novel approach to visual search in e-commerce fashion using siamese neural network and multi-scale cnn," in *2023 International Electronics Symposium (IES)*. Denpasar, Indonesia: IEEE, Aug 2023, pp. 460–465.

[4] H. Li *et al.*, "Date: Domain adaptive product seeker for e-commerce," in *2023 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*. Vancouver, BC, Canada: IEEE, Jun 2023, pp. 19 315–19 324.

[5] K. Li, J. Zhang, and D. Forsyth, "Povnet: Image-based virtual try-on through accurate warping and residual," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 45, no. 10, pp. 12 222–12 235, Oct 2023.

[6] B. Fele, A. Lampe, P. Peer, and V. Struc, "C-vton: Context-driven image-based virtual try-on network," in *2022 IEEE/CVF Winter Conference on Applications of Computer Vision (WACV)*. Waikoloa, HI, USA: IEEE, Jan 2022, pp. 2203–2212.

[7] I. Bansal, S. Dhar, Yuvraj, Gitanjali, and Nikam, "A framework and techniques for image-based search application with an e-commerce domain," in *2021 5th International Conference on Trends in Electronics and Informatics (ICOEI)*. Tirunelveli, India: IEEE, Jun 2021, pp. 1102–1109.

[8] H. Zhong and Y. Wang, "A product recommendation method by analyzing images and reviews in e-commerce," in *2021 IEEE 10th Global Conference on Consumer Electronics (GCCE)*. Kyoto, Japan: IEEE, Oct 2021, pp. 934–935.

[9] A. Pande, R. Biswas, P. Chennu, H. N, and A. Joshi, "Real-time personalized guest experiences using product attribute information on vanilla hardware," in *2023 IEEE 39th International Conference on Data Engineering Workshops (ICDEW)*. Anaheim, CA, USA: IEEE, Apr 2023, pp. 28–35.

[10] A. G. A. G, 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)*. Bangalore, India: IEEE, Jun 2024, pp. 1–5.

[11] V. C. Sharmila, Suryadevi, P. S. Lakchudha, and K. Seervi, "Conversational chabot builder-smarter virtual assistants with domain specified ai," in *2024 Ninth International Conference on Science Technology Engineering and Mathematics (ICONSTEM)*. Chennai, India: IEEE, Apr 2024, pp. 1–7.

[12] P. A. Olujimi and A. Ade-Ibijola, "Nlp techniques for automating responses to customer queries: a systematic review," *Discov Artif Intell*, vol. 3, no. 1, p. 20, May 2023.

[13] R. Licapa-Rodriguez, J. Gomez-Ramos, and D. Mauricio, "Ecobot: Virtual assistant for e-commerce of ecological bricks based on facebook messenger," in *2021 IEEE Engineering International Research Conference (EIRCON)*. Lima, Peru: IEEE, Oct 2021, pp. 1–4.

[14] N. K. Kumar, K. Maheswari, A. Abinaya, J. Ramya, P. K. Ande, and C. P. Ramaian, "Advancements in chatbot technology for enhanced customer support in online retail," in *2024 Ninth International Conference on Science Technology Engineering and Mathematics (ICONSTEM)*. Chennai, India: IEEE, Apr 2024, pp. 1–6.

[15] A. Shams, D. F. Nugroho, M. Hummel, B. Quattelbaum, C. Breckenfelder, and S. Julidayani, "5garderobe: A scalable real-time virtual wardrobe & e-commerce solution," in *2024 International Conference on Artificial Intelligence, Computer, Data Sciences and Applications (ACDSA)*. Victoria, Seychelles: IEEE, Feb 2024, pp. 1–6.

[16] C. C. Sahoo, D. S. Tomar, and J. Bharti, "Transformer based multimodal similarity search method for e-commerce platforms," in *2023 IEEE Guwahati Subsection Conference (GCON)*. Guwahati, India: IEEE, Jun 2023, pp. 01–06.

[17] R. Namboodiri, K. Singla, and V. Kulkarni, "Gan based try-on system: Improving cagan towards commercial viability," in *2021 12th International Conference on Computing Communication and Networking Technologies (ICCCNT)*. Kharagpur, India: IEEE, Jul 2021, pp. 1–6.

[18] S. Majithia, S. N. Parameswaran, S. Babar, V. Garg, A. Srivastava, and A. Sharma, "Robust 3d garment digitization from monocular 2d images for 3d virtual try-on systems," in *2022 IEEE/CVF Winter Conference on Applications of Computer Vision (WACV)*. Waikoloa, HI, USA: IEEE, Jan 2022, pp. 1411–1421.

[19] V. K. K. Rejeti, S. Abdul, P. H. Prasanth, S. Ashok, and S. M. Sameer, "Virtual fit using computer vision and trimesh," in *2023 Second International Conference on Electronics and Renewable Systems (ICEARS)*. Tuticorin, India: IEEE, Mar 2023, pp. 1590–1595.

[20] N. Afifah and W.-T. Wang, "Exploring the use of the delphi method in visual search service effectiveness measurement research in e-commerce platform," in *2023 International Conference on Software and System Engineering (ICoSSE)*. Marseille, France: IEEE, Apr 2023, pp. 52–56.

[21] R. El Youbi, F. Messaoudi, and M. Loukili, "Machine learning-driven dynamic pricing strategies in e-commerce," in *2023 14th International Conference on Information and Communication Systems (ICICS)*. Irbid, Jordan: IEEE, Nov 2023, pp. 1–5.

[22] B. S. Rochana and S. Juliet, "Virtual dress trials: Leveraging gans for realistic clothing simulation," in *2024 3rd International Conference on Artificial Intelligence For Internet of Things (AIIoT)*. Vellore, India: IEEE, May 2024, pp. 1–6.

[23] J. Qu, "Research on vegetable replenishment and pricing strategies for supermarkets based on time series and multi-objective planning," in *2024 IEEE 2nd International Conference on Control, Electronics and Computer Technology (ICCECT)*. Jilin, China: IEEE, Apr 2024, pp. 614–618.

[24] D. Sudharson, A. K. Dubey, A. B. Kumar, S. J. Thrishna, N. F, and S. K. Kavinaya, "A novel ai framework for personalisation and customization of product prices through bigdata analytics," in *2023 International Conference on Artificial Intelligence and Knowledge Discovery in Concurrent Engineering (ICECONF)*. Chennai, India: IEEE, Jan 2023, pp. 1–6.

[25] C. P. Gupta, V. V. R. Kumar, and A. Khurana, "Artificial intelligence application in e-commerce: Transforming customer service, personalization and marketing," in *2024 11th International Conference on Computing for Sustainable Global Development (INDIACom)*. New Delhi, India: IEEE, Feb 2024, pp. 10–16.

[26] D.-N. Nguyen, V.-H. Nguyen, T. Trinh, T. Ho, and H.-S. Le, "A personalized product recommendation model in e-commerce based on retrieval strategy," *Journal of Open Innovation: Technology, Market, and Complexity*, vol. 10, no. 2, p. 100303, Jun 2024.