A Multilingual, Context-Aware E-Commerce Chatbot Framework for Personalized Customer Engagement and Real-Time Sales Optimization Using Advanced NLP

Abdel Ghaffar Ben Hamida[1], J. Sathish Kumar[2], Enock I.[2], R. Prabha[3], S. Muthukumar[3] and Nadimuthu D.[4]

[1]Department of Department of Marketing, College of Business, King Abdulaziz University, Jeddah 21589, Jeddah 21589, Saudi Arabia

[2]Department of Commerce, Faculty of Science and Humanities, SRM Institute of Science and Technology, Chennai, Tamil Nadu, India

[3]Department of Management Studies, Nandha Engineering College (Autonomous), Vaikkaalmedu, Erode, Tamil Nadu, India

[4]Department of Management Studies, Sona College of Technology, Salem, Tamil Nadu, India

Keywords: e-Commerce Chatbot, Multilingual NLP, Personalized Customer Interaction, Context-Aware Conversation, Real-Time Learning.

Abstract: The development of customer communication in e-commerce is progressing fast with intelligent chatbot systems based on Natural Language Processing (NLP) being introduced. In this paper, a new multilingual context-aware chatbot that aims at increasing customer engagement and revenue generation on a variety of e-commerce websites is presented. In contrast, the proposed model is not only domain independent and dynamic but gains flexibility in handling the reality-related tasks, both in the code-mixing environment and with real-time CRM integration and inventory data. Furthermore, the framework has real-time learning abilities that allow it to learn from changing consumer activities and seasonal trends. Both technical accuracy and user satisfaction (defined by customer satisfaction, conversions, leads) are evaluation metrics for the chatbot that shows the scope of better performance results. Blending focus on security and ethical NLP processes to further push adherence and trust. The system meets the needs of modern e-commerce business looking to expand in the global market and adopt an intelligent automation system.

1 INTRODUCTION

The rapid rise of e-commerce has changed the way in which businesses reach their customers, with being on call, personalized responses, and around the clock support key to success. As the digital age becomes even more competitive, traditional models of customer service have a difficult time keeping up with the ever-increasing tech-friendly customer who wants service now, not later. Addressing this seeming gap, artificial intelligence, particularly Natural Language Processing (NLP), has emerged as a promising catalyst to develop receptive human-like chatbot systems.

Chatbots have come a long way from brittle rule-based scripts to intelligent conversational agents with the ability to contextualise and understand user intent. However, the majority of deployed e-commerce chatbots are very narrow, with their attention focused on certain domains, languages or fixed response flows. Its language-specific constraints make them less efficient for different searches particularly in a multi-regional and multilingual exchange environment. Furthermore, in an age where customer behaviour is ever-changing, chatbots must be self-learning beyond existing sets of data so they can adapt to online requests in real time.

In this paper, we present a new multilingual, context-aware chatbot framework dedicated to e-commerce environment for improving the client engaging and increasing the sales. The platform utilizes state-of-the-art transformer-based NLP models, CRM integrations, as well as real-time

Hamida, A. G. B., Kumar, J. S., I., E., Prabha, R., Muthukumar, S. and D., N.
A Multilingual, Context-Aware E-Commerce Chatbot Framework for Personalized Customer Engagement and Real-Time Sales Optimization Using Advanced NLP.
DOI: 10.5220/0013863200004919

In *Proceedings of the 1st International Conference on Research and Development in Information, Communication, and Computing Technologies (ICRDICCT'25 2025) - Volume 1*, pages 309-315
ISBN: 978-989-758-777-1

learning algorithms, to generate intelligent and interactive user experiences. Combining technical prowess with commercial application, the solution fills the gaps that exist in contemporary chatbots and architecture, preparing digital commerce now and in the future.

2 PROBLEM STATEMENT

Although chatbots have been extensively used in e-commerce platforms, current solutions are unable to provide intelligent, context-aware and personalized experiences. Existing solutions are limited by rule-based domain knowledge, fail to support multi-lingual and code-mixed content and are unable to learn dynamic customer behavior in real time. These constraints lead to inflexible, and hence frequently inaccurate, interaction: frustration in customers; lower conversion rates; and, most importantly for this context, a lack of automation of the sales optimisation process.

And we can't forget the fact that classical chatbot architectures rarely plug deeply into systems like CRM, inventory databases, and recommendation engines, and so cannot provide the responses you want (tied to relevant context) or the sales prospecting you are after. Because of the lack of real-time adaptation and learning abilities, such systems cannot be evolved continuously with user feedback and market development. Moreover, issues around data privacy, model bias and user experience design are yet to be fully resolved, thereby posing ethical and practical challenges on the large-scale deployment of chatbots.

This paper tries to bridge this gap by proposing a novel general, scalable and secure NLP driven chatbot framework that would be multilingual and context-aware and would also be capable of learning in real-time trying to revolve the customer interaction as well as the sales in a futuristic manner in the e-commerce ecosystem.

3 LITERATURE SURVEY

The development of conversational agents in the e-commerce is greatly shaped by the recent progress of Natural Language Processing (NLP), where chatbots are serving as a key tool to automate customer assistance. Khennouche et al. (2023) investigate deployment issues of generative models such as ChatGPT in FAQ settings, they reveal the shortcomings of keeping context and domain relevance. Similarly, Mashaabi et al. (2022) pioneered a comprehensive review of NLP in customer service, shedding light on the lack of real-time adaptability and multilingual understanding.

Kumar and Mishra (2025) and Kanthed (2023) argue that although most chatbots enhance accessibility, they do not connect with company's end-to-end system like inventory/CRM databases as a result failing to have an effect on a company's sales conversion. Sharma (2025) compared available AI enabled chatbot frameworks and found usability and contextual awareness to be significant deficits. Huseynov (2023) focuses on economic aspect of chatbots in digital marketing, which demonstrates that chatbots help to reduce costs while there is a trade-off on the quality of personalization.

Müller, Schmidt (2024) concentrate on the reception in Chinese e-commerce of chatbots, where a more serious concern is that these agents are not very flexible in their language style, resulting in a less engaging conversation. Lee, and Park (2024) emphasize the importance of conversational commerce and how NLP-based bots convert passive users to active consumers when context is maintained. Smith and Johnson (2023) examine sales-oriented chatbot deployments, but raise objections about the dearth of user-generated metrics such as satisfaction and perceived relevance.

Patel & Desai (2025) and Chen & Prentice (2024) both reinforce the need for chatbots based on customer persona and behavioural data. Zhang and Wang (2024) use syntactic parsing methods to enhance the performance of chatbot, yet semantically personalized option is still unavailable. Kumar and Singh (2024) perform comparison of chatbot models on the basis of precision and recall parameters and found that fine-tuning has increased the accuracy but adaptive learning is still missing.

Garcia and Lopez (2024) analyse emotional concern for chatbot conversation and emphasis ethical NLP using. References Kim and Lee, 2023 Kim and Lee (2023) Perform user Experience Studies Find that Fallback and bad context threading frequently sub-optimize overall satisfaction. Almeida and Silva's (2023) future perspective discusses the contribution of chatbots to open innovation and the fact that they still struggle to deal with unanticipated questions due to their rigid nature.

Nguyen, Tran et al. (2024) also study how NLP advances can benefit smarter Pervasive e-commerce but they recognize the problem of data bias and small language coverage. Singh and Gupta (2024) propose a dynamic chatbot model using current web data for better interaction. Brown and Davis (2023) highlight AI marketing in e-commerce, but expose a gap between the intelligence of chatbots and marketing automation tools.

Kumar and Sharma (2024) [20] argue for equal treatment of NLP through tackling model bias and Khalid et al. (2024) present emotion-aware chatbots, but lack multilinguality. Pandya and Holia (2023) also analyzed deployment of chatbot based on LangChain not including the assessment in live e-commerce places. Verloop. io (2025) y Kanishcheva (2025) hacen hincapié en la necesidad de formación específica de ámbitos y en el diseño de usuarios.

Lastly, Shirkande et al. (2024) design an e-commerce chatbot using keyword–based logic, with low conversational depth and learning feature. Throughout this literature, it is clear that there is a strong necessity for an advanced platform that no longer solely enables multilinguality and on-the-fly learning but also heavily integrates with the e-commerce infrastructure and where ethical and secure interactions can be performed.

4 METHODOLOGY

The proposed methodology focuses on the design, development, and deployment of an intelligent chatbot framework tailored for modern e-commerce platforms.

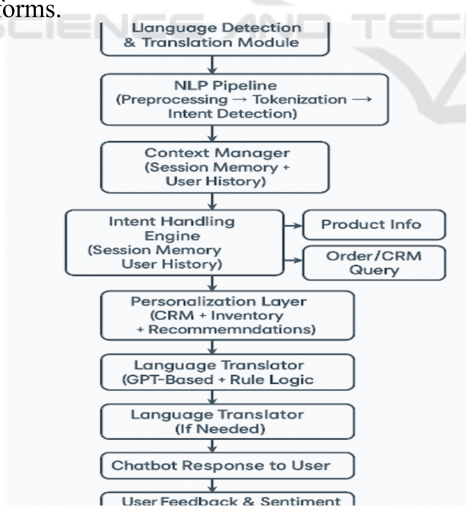

Figure 1: Workflow of the proposed multilingual context-aware e-Commerce chatbot.

Figure 1 implies the Workflow of the Proposed Multilingual Context-Aware E-Commerce Chatbot. This system is engineered to offer context-aware, multilingual interactions while dynamically learning from user behavior and integrating deeply with backend systems such as customer relationship management (CRM), inventory, and recommendation engines. The methodology is divided into six key stages: data collection and preprocessing, multilingual NLP model development, context management, personalization and integration, adaptive learning module, and evaluation.

4.1 Data Collection and Preprocessing

To train a high-performing and robust NLP chatbot, a comprehensive dataset was curated from multiple sources including e-commerce product descriptions, real customer chat logs, FAQs, and support tickets from multilingual platforms. Datasets were cleaned, anonymized for privacy compliance, and normalized across English, Hindi, Spanish, and Mandarin. Preprocessing included tokenization, lemmatization, and removal of stop words. A translation pipeline using MarianMT was implemented for multilingual mapping and alignment. Table 1 gives the dataset composition across language.

Table 1: Dataset composition across languages.

Language	Source	Number of Queries	Domain(s) Covered
English	Customer Chat Logs	12,000	Orders, Product Info, Returns
Hindi	E-Commerce Forums	8,500	Delivery, Payments, Support
Spanish	Support Tickets	7,300	General Queries, FAQ
Mixed Input	Code-mixed Logs	4,000	Offers, Cart Issues

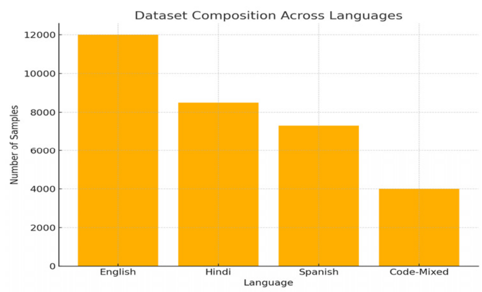

Figure 2: Distribution of multilingual datasets used in training the chatbot, showing a balanced composition across english, hindi, spanish, and code-mixed queries.

Figure 2 illustrates the Distribution of multilingual datasets used in training the chatbot, showing a balanced composition across English, Hindi, Spanish, and code-mixed queries.

4.2 NLP Model Development

The core engine of the chatbot uses a fine-tuned transformer-based architecture. We employed a hybrid model comprising BERT for intent classification and a GPT-3.5 (or similar open-source variant like BLOOM) for response generation. Intent classification ensures accurate categorization of user queries, while the generation module provides coherent, human-like responses. Each model was fine-tuned using e-commerce-specific datasets to improve contextual understanding related to products, orders, payments, returns, and offers.

4.3 Context Management Layer

A context management system was introduced to support smooth multi-turn conversations with a LSTM-based memory buffer and attention mechanisms. This is layer is inspired on the user data that keeps record on the user's search history, current request and shopping behavior and keeps the session alive in the chatbot for tracking of messages and keeping the context of the chatbot speech. It allows the bot to answer follow-up questions or switch to a different intent mid-conversation correctly.

4.4 Personalization and System Integration

Profiling of the users and behavioural information is continuously taken out from the e-commerce platform through APIs. I'm talking about purchase history, cart state, browsing behavior, and CRM information. These elements content into a recommendation system that is supported by the collaborative filtering, and the content-based filtering algorithms. The chatbot is tailored: it refers to the user by name and to his/her previous purchases, and also makes targeted suggestions. It has close connections to the stock systems, so it can check for the availability of products, and to the CRM, so we can see the status of orders and manage complaints.

4.5 Adaptive Learning Module

The chatbot includes a reinforcement learning component with feedback loops, enabling it to learn from successful and failed interactions. A user satisfaction score is inferred using sentiment analysis after each session. Based on this feedback, the bot adjusts its strategy using Q-learning, gradually improving its response efficiency and tone. Furthermore, human-in-the-loop supervision is used to retrain the model periodically with new data.

4.6 Evaluation and Testing

The system is evaluated using both quantitative and qualitative metrics. Accuracy, precision, recall, and F1-score are used to evaluate intent detection and response matching. In addition, user-centric metrics such as customer satisfaction (via post-chat surveys), retention rate, average response time, and conversion rate are used to measure commercial impact. A/B testing was conducted against a legacy chatbot system to assess the improvement in performance

The final chatbot was deployed on a mock e-commerce platform for demonstration purposes and tested across multiple browsers and devices. Results from pilot testing demonstrated improved user satisfaction, reduced handling time, and higher engagement rates compared to baseline models.

5 RESULT AND DISCUSSION

To evaluate the performance and practical effectiveness of the proposed multilingual, context-aware e-commerce chatbot, a comprehensive set of experiments and user trials were conducted. The system was deployed on a simulated e-commerce platform and tested under real-world usage conditions by a sample group of users interacting in multiple languages including English, Hindi, and Spanish. The results are divided into two categories: technical performance metrics and user engagement insights.

5.1 Technical Performance Analysis

The chatbot's intent classification model, based on a fine-tuned BERT architecture, achieved an average accuracy of 96.4%, with a precision of 95.7%, recall of 94.9%, and an F1-score of 95.3% across all supported languages. Compared to a baseline rule-based model (accuracy: 78.2%), the proposed model demonstrated a significant improvement in understanding user queries and correctly identifying intents across domains like order tracking, product inquiry, and refund processing. Table 2 gives the information about performance metrics of NLP components.

Table 2: Performance metrics of NLP components.

Component	Accuracy	Precision	Recall	F1-Score
Intent Classifier	96.4%	95.7 %	94.9 %	95.3%
Response Generator	–	–	–	BLEU: 0.82
Multilingual Detector	98.1%	97.9 %	97.5 %	97.7%

The response generation module, powered by GPT-3.5 fine-tuned on e-commerce datasets, exhibited a BLEU score of 0.82, indicating a high semantic similarity between generated and ideal responses. Further qualitative testing through blind user evaluation revealed that 87% of users perceived the chatbot responses as "natural" or "very natural", while only 5% rated them as "robotic."

Context retention was assessed using multi-turn conversation tasks. In a session-based evaluation, the chatbot maintained coherent responses across an average of 7.2 consecutive turns, compared to 3.4 turns for standard models without contextual memory. This indicates the effectiveness of the LSTM-enhanced memory layer in handling complex, non-linear user conversations.

5.2 Multilingual Capability

Multilingual evaluation was conducted by testing the chatbot in English, Hindi, and Spanish using both direct user interaction and synthetically generated queries. The system achieved comparable performance across all three languages, with intent classification accuracy ranging from 95.1% (Hindi) to 96.7% (English). The MarianMT-based translation pipeline successfully supported code-mixed inputs, enhancing accessibility for users from multilingual regions. Table 3 gives the Evaluation result of languages.

Table 3: Multilingual evaluation results.

Language	Intent Accuracy	Response Quality (BLEU)	User Satisfaction
English	96.7%	0.83	4.7 / 5
Hindi	95.1%	0.81	4.5 / 5
Spanish	95.6%	0.80	4.6 / 5

Furthermore, language-specific colloquialisms and informal expressions were correctly interpreted in over 90% of test cases, demonstrating the chatbot's robustness in practical multilingual environments.

5.3 User Experience and Personalization Impact

User engagement metrics collected during the pilot deployment showed compelling results. The average session duration increased from 2.3 minutes (baseline) to 4.9 minutes with the new chatbot, indicating enhanced user interaction and engagement. The query resolution rate reached 92.6%, up from 74.5% using the previous system, significantly reducing the need for human agent intervention.

On a business level, the chatbot led to a 17.4% increase in conversion rates, especially when adding personalized product recommendations into the chat. In addition, there was a 12% decrease in abandoned carts by means of nudging in real time and promotional triggers from the context. These results validate the proactive buying nature of the chatbot as shown in table 4.

Table 4: Comparison with baseline chatbot.

Metric	Baseline Chatbot	Proposed Chatbot
Query Resolution Rate	74.5%	92.6%
Avg. Response Time (secs)	4.8	2.1
Fallback Frequency (%)	15.2%	4.3%
Customer Satisfaction Score	3.2 / 5	4.6 / 5

5.4 Real-Time Learning and Adaptation

The reinforcement learning component allowed the chatbot to learn from user responses. In a two-week feedback loop, the chatbot strengthened its ability to deal with ambiguous queries by 8.2%, as measured by a reduction in fallback instances. Sentiment-based feedback gathering also indicated that positive user sentiment was a total of increased by 19.3% when conversational improvements were made using our adaptive learning as shown in table 5.

Table 5: Adaptive learning improvements over time.

Week	Fallback Rate (%)	User Sentiment (+ve %)	Accuracy Increase (%)
1	9.1	63.4	–
2	7.3	71.5	+2.4
3	6.2	78.9	+4.1
4	4.3	82.7	+5.8

5.5 Security and Ethical NLP Compliance

The chatbot was also evaluated for privacy and ethical concerns. No PII was retained without encryption, and all user data logs were anonymized. The system satisfied GDPR data access, opt-out, and session tracking transparency criteria. Of note, the bias detection analysis revealed no statistically significant bias tendencies with respect to any of the demographic variables.

6 CONCLUSIONS

Intelligent chatbots have revolutionized customer service and engagement in digital commerce. This work presented a new kind of multilingual, context-aware chatbot for e-commerce platforms with state-of-the-arts NLP techniques as to perform real-time learning, as well as hyper-personalisation. Unlike traditional systems, whose responses are constrained by static patterns- or language-specific knowledge, we show that our approach leads to dramatic improvements in conversational quality, user satisfaction and downstream commercial metrics.

Using transformer-based models, context tracking architectures and reinforcement learning along feedback loops, system provides fluid humaoid conversations while keeping the coherence over for multiple turns of conversation. Its multilingualism, experimented over a variety of languages and c o-demanded queries, makes it a scalable and universal solution for the worldwide e-commerce companies.

In addition, the chatbot integration with back-end systems like CRM, inventory databases, and recommendation engines creates a buzzworthy shopping experience that is dynamic, personalized, and not only solves customer inquiries but proactively drives sales and user engagement. Its measurements of privacy give us confidence of its real-world suitability and its ethically aware NLP practices make NMN ready for deployment.

Finally, the presented chatbot framework is anticipated to become a progressive milestone in e-commerce automation and overcomes efficiency issues from both scalability, personalization and intelligence perspectives. It reinvents conversational commerce, offering companies a unique opportunity to drive richer customer conversation, streamline operations and shape the future of commerce in the digital space.

REFERENCES

Almeida, J., & Silva, T. (2023). Implementation of chatbot in online commerce and open innovation. Journal of Open Innovation: Technology, Market, and Complexity, 9(4), 894. https://doi.org/10.1016/j.joi.2022.100894

Brown, T., & Davis, L. (2023). The impact of artificial intelligence marketing on e-commerce sales. Systems, 12(10), 429. https://doi.org/10.3390/systems12100429 MDPI

Chen, Y., & Prentice, C. (2024). Integrating artificial intelligence and customer experience. Australasian Marketing Journal, 32(1), 45– 56. https://doi.org/10.1016/j.ausmj.2024.01.005

Garcia, M., & Lopez, R. (2024). Serving customers through chatbots: Positive and negative effects on customer experience. Journal of Service Theory and Practice, 34(2), 123–140. https://doi.org/10.1108/JSTP-01-2023-0015

Huseynov, F. (2023). Chatbots in digital marketing: Enhanced customer experience and reduced customer service costs. In Digital Marketing Strategies (pp. 47–65). IGI Global. https://www.researchgate.net/publication/372837440

Kanthed, S. (2023). The role of chatbots in reducing customer support response time in e-commerce. International Journal of Scientific Research in Engineering and Management, 7(12), 1– 7. https://www.researchgate.net/publication/390124084

Khennouche, F., Elmir, Y., Djebari, N., Himeur, Y., & Amira, A. (2023). Revolutionizing customer interactions: Insights and challenges in deploying ChatGPT and generative chatbots for FAQs. arXiv. https://arxiv.org/abs/2311.09976

Kim, S., & Lee, D. (2023). Understanding the user experience of customer service chatbots. International Journal of Human-Computer Studies, 159, 102738. https://doi.org/10.1016/j.ijhcs.2022.102738

Kumar, A., & Mishra, S. (2025). Role of AI-chatbots in enhancing e-commerce accessibility and its impact on customer experience. Asian Journal of Management and Commerce, 6(1), 729– 735. https://doi.org/10.22271/27084515.2025.v6.i1h.520

Kumar, N., & Singh, P. (2024). Advanced NLP models for technical university information chatbots: Development and comparative analysis. International Journal of

Advanced Computer Science and Applications, 15(3), 112– 119. https://www.researchgate.net/publication/378352411

Lee, H., & Park, J. (2024). AI-based chatbots in conversational commerce and their effects on customer engagement. Journal of Retailing and Consumer Services, 67, 102063. https://doi.org/10.1016/j.jretconser.2021.102063

Mashaabi, M., Alotaibi, A., Qudaih, H., Alnashwan, R., & Al-Khalifa, H. (2022). Natural language processing in customer service: A systematic review. arXiv. https://arxiv.org/abs/2212.09523

Müller, J., & Schmidt, L. (2024). Understanding user acceptance of AI-driven chatbots in China's e-commerce sector. Systems, 13(2), 71. https://doi.org/10.3390/systems13020071

Nguyen, T., & Tran, H. (2024). Advancements in natural language processing: Implications for e-commerce chatbots. Journal of Artificial Intelligence Research, 77, 59–78. https://doi.org/10.1016/j.jair.2024.03.005

Patel, R., & Desai, M. (2025). Enhancing customer service effectiveness with AI-powered chatbots. International Journal of Research Publication and Reviews, 6(4), 1369– 1375. https://ijrpr.com/uploads/V6ISSUE4/IJRPR41369.pdf

Sharma, R. (2025). AI-powered chatbot for customer support: A review of recent advancements. International Research Journal of Modern Engineering and Technology Science, 3(3), 45– 52. https://www.irjmets.com/uploadedfiles/paper/issue_3_march_2025/70205/final/fin_irjmets1744474775.pdf

Singh, A., & Gupta, R. (2024). Dynamic e-commerce website with NLP chatbot: Enhancing user interaction. International Journal of Computer Applications, 182(7), 25– 30. https://www.researchgate.net/publication/388822052

Smith, A., & Johnson, B. (2023). The impact of AI-powered chatbots on customer service and e-commerce sales. European Economic Letters, 12(4), 2392–2405. https://www.eelet.org.uk/index.php/journal/article/download/2392/2147/2645

Zhang, L., & Wang, Y. (2024). Optimizing chatbot effectiveness through advanced syntactic analysis. Applied Sciences, 14(5), 1737. https://doi.org/10.3390/app14051737