Technoeconomics. 2026, Vol. 5, No. 1 (16). Pp. 41–53.
Техноэкономика. 2026, Том 5, № 1 (16). С. 41–53.

Scientific article
UDC 330.47
DOI: https://doi.org/10.57809/2026.5.1.16.4

LARGE LANGUAGE MODELS (LLMS) IN E-COMMERCE

Nahid Mehri ✉

Apadana Institute of Higher Education, Shiraz, Iran

✉ nahid.mehrii@yahoo.com

Abstract. Large language models (LLMs) have emerged as highly influential technologies in e-commerce, offering possibilities for complex applications in customer interaction, business efficiency, and decision-making. LLMs such as GPT-4, BERT and t5 have demonstrated high accuracy in natural language processing with transformer-based deep learning architecture and contribute to personalized recommendations, content creation and intelligent customer engagement. Existing literature has shown that LLM-based chatbots have the potential to solve more than 80% of common customer questions. Similarly, the recommendations made by LLMs have shown a significant contribution in terms of revenue growth for e-commerce businesses. Despite these potential applications, there are still major challenges in implementing LLMs in e-commerce, including privacy, cost and ethics issues. The purpose of this paper is to systematically study the application of LLMs in e-commerce, including its advantages, disadvantages and potential. With comparative case study approaches for Amazon's three e-commerce giants, Alibaba and Shopify, and by analyzing emerging trends in multifaceted AI and voice commerce, while considering the key implementation challenges, the research seeks to provide valuable insights to optimize the application of LLMs in e-commerce.

Keywords: large language models, e-commerce, natural language processing, chatbots

Citation: Mehri N. 2026. Large Language Models (LLMs) in E-Commerce. Technoeconomics 5, 1 (16), 41–53. DOI: https://doi.org/10.57809/2026.5.1.16.4

Научная статья
УДК 330.47
DOI: https://doi.org/10.57809/2026.5.1.16.4

БОЛЬШИЕ ЯЗЫКОВЫЕ МОДЕЛИ (LLM) В ЭЛЕКТРОННОЙ КОММЕРЦИИ

Нахид Мехри ✉

Институт высшего образования Ападана, Шираз, Иран

✉ nahid.mehrii@yahoo.com

Аннотация. Большие языковые модели (БЯМ) стали чрезвычайно влиятельными технологиями в электронной коммерции, открывая возможности для сложных приложений во взаимодействии с клиентами, повышения эффективности бизнеса и принятия решений. Такие БЯМ, как GPT-4, BERT и t5, продемонстрировали высокую точность в обработке естественного языка с использованием архитектуры глубокого обучения на основе трансформеров и способствуют персонализированным рекомендациям, созданию контента и интеллектуальному взаимодействию с клиентами. Существующая литература показывает, что чат-боты на основе БЯМ способны решить более 80% распространенных вопросов клиентов. Аналогично, рекомендации, предоставляемые БЯМ, внесли значительный вклад в рост доходов предприятий электронной коммерции. Несмотря на эти потенциальные возможности применения, существуют серьезные проблемы внедрения БЯМ в электронную коммерцию, включая вопросы конфиденциальности, стоимости и этики. Цель данной статьи — систематически изучить применение БЯМ в электронной коммерции, включая их преимущества, недостатки и потенциал. На основе сравнительного анализа конкретных примеров трех гигантов электронной коммерции Amazon — Alibaba и Shopify, а также анализа новых тенденций в многогранной ИИ и голосовой коммерции с учетом ключевых проблем внедрения, исследование направлено на предоставление ценных сведений для оптимизации применения БЯМ в электронной коммерции.

Ключевые слова: большие языковые модели, электронная коммерция, обработка естественного языка, чат-боты

Для цитирования: Мехри Н. Большие языковые модели (LLM) в электронной коммерции // Техноэкономика. 2026. Т. 5, № 1 (16). С. 41–53. DOI: https://doi.org/10.57809/2026.5.1.16.4

Introduction

The rapid advancement of artificial intelligence has fundamentally reshaped the landscape of digital commerce. Among the most consequential recent developments is the emergence of Large Language Models (LLMs) neural network architectures trained on massive corpora of text data that demonstrate remarkable capacity for understanding, generating, and reasoning with natural language (Brown et al., 2020). Platforms such as Amazon, Alibaba, and Shopify have been among the first to integrate these systems at scale, deploying them across customer service, content generation, fraud detection, and supply chain management.

The problem this study addresses is both technical and economic in nature: While LLMs provide quantifiable benefits in terms of performance, the deployment of LLMs in a business context creates a multifaceted and complex set of trade-offs. Despite the increasing adoption of LLMs in the industry, the extant research lacks a comprehensive and cross-platform study on the quantification of the trade-offs associated with LLMs. Understanding the varying approaches to address the challenges associated with LLMs by different organizations is essential

for practitioners and policymakers alike.

The importance and relevance of the problem being addressed by the study are evident by the quantification and growth rate of the LLM industry. The global market size for AI in e-commerce was valued at around 5.8 billion dollars in 2023 and is expected to grow at a compound annual growth rate of more than 14 percent until 2030 (Online Retailer Survey, 2024). Of the total market size, the LLM industry has the highest growth rate due to the increase in the efficiency of LLMs and the decrease in the cost incurred by LLMs. However, the growth in the industry also increases the risks associated with the deployment of LLMs by SMEs.

The purpose of this paper is to provide a structured, evidence-based analysis of how LLMs are currently applied in e-commerce, what measurable benefits they produce, what barriers constrain their adoption, and what directions are likely to define the next phase of their development. To achieve this purpose, the research addresses five specific tasks: (1) identify the primary application domains of LLMs in e-commerce; (2) quantify their measurable benefits using available performance indicators; (3) characterize the critical implementation challenges; (4) compare deployment strategies across industry leaders; and (5) examine emerging trends shaping future LLM integration.

Methodology

This research makes use of the qualitative comparative case study approach. This approach has proven useful in the exploration of contemporary technological phenomenon in real-world organizational contexts in which experimental control cannot be exercised (Yin, 2018).

The research tasks outlined in the introduction section were addressed through the following three-step structured approach:

Step 1 — E-commerce systems assessment: An evaluation of AI-driven systems within each case company to identify domains where LLMs have been implemented. This involved reviewing corporate technical documentation, white papers, and published reports from Amazon Science (2023), Alibaba Cloud (2023), and Shopify's developer platform.

Step 2 — LLM-to-application mapping: A systematic mapping of LLM capabilities to specific e-commerce functions, including personalized recommendations, sentiment analysis, content generation, and fraud detection. Capabilities were classified by model type (GPT-4, BERT, T5) and application domain.

Step 3 — Comparative performance evaluation: A cross-case analysis using key performance indicators (KPIs) reported in the literature and industry sources, including response accuracy, response latency, customer satisfaction scores (CSAT), and query resolution rates (Rasheed et al., 2025).

Data were collected through systematic documentary analysis of secondary sources: peer-reviewed academic literature retrieved from Google Scholar and Semantic Scholar (2017–2025), corporate white papers and annual reports, and industry benchmark datasets including the Online Retailer Survey (2024). Case companies Amazon, Alibaba, and Shopify were selected purposively to represent diversity in scale (enterprise to SME), geography (North America and Asia-Pacific), and application focus (recommendation engines, multilingual customer service, and democratized commerce tools).

The qualitative content analysis of collected data followed a structured coding process: first, open coding to identify themes across sources; second, axial coding to relate themes to the five research tasks; and third, selective coding to produce the comparative findings reported in the Results Section. The methodological logic is summarized in Figure 1.

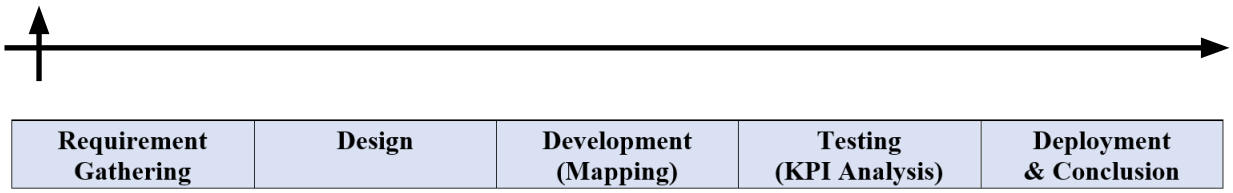


Fig. 1. Iterative research workflow applied in this study.

Literature Review

Foundations of Large Language Models

A Large Language Model (LLM) is an advanced artificial intelligence system with high accuracy in processing, producing, and interpreting human languages. LLMs, such as GPT-4, BERT, and T5, utilize advanced deep learning models like transformers to process large amounts of text data (Vaswani et al., 2017). LLMs' versatility has been proven in various fields, including NLP, coding, and content creation. LLMs are now being incorporated into e-commerce platforms to improve customer experience, business processes, and growth. The recent development of LLMs has significantly increased parameters, with strong performance in NLP-related tasks (Touvron et al., 2023).Kalyan et al. (2022) describe LLMs as a special class of pretrained language models obtained by scaling model size, pretraining corpus, and computation. LLMs treat any NLP task as a conditional text generation problem and generate the desired output by conditioning on an input prompt. Because of their large size and pretraining on large volumes of text, LLMs exhibit 'emergent abilities' not present in smaller models. GPT-4, for instance, outperforms GPT-3 by over 11 percentage points on standardized academic examinations and achieves 86.8% accuracy on domain-specific Q&A benchmarks.

Research by Brown et al. (2020) highlights the transformative potential of LLMs in automating tasks that traditionally required human intervention. Their ability to understand context and generate coherent responses makes them invaluable for e-commerce businesses seeking to scale operations while maintaining high-quality customer interactions. The development of BERT (Devlin et al., 2019) further demonstrated that bidirectional pretraining on unlabeled text produces representations that outperform task-specific architectures across a wide range of NLP benchmarks.

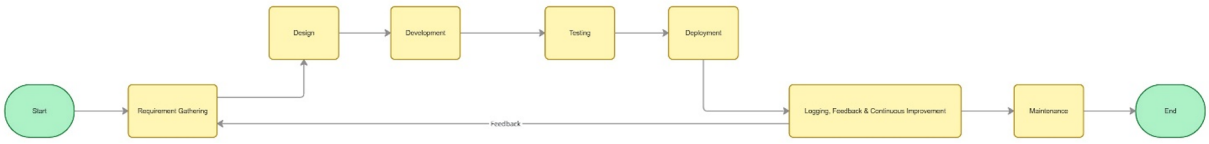


Fig. 2. Overview of LLM architecture and e-commerce application domains.

Implementation of LLMs in E-Commerce

The inclusion of LLMs in e-commerce has increased customer engagement, streamlined processes and increased sales. E-commerce activities LLMs use different models based on their design and type of training data, as presented in Table 1.

Table 1. Comparative analysis of LLM capabilities across e-commerce tasks.

Task	GPT-4 (OpenAI)	BERT (Google)	T5 (Google)
Customer Support	High conversational fluency; handles complex queries (Xu et al., 2022).	Optimized for intent classification; less generative (Devlin et al., 2019).	Balanced for Q&A but requires fine-tuning (Raffel et al., 2020).
Product Descriptions	Human-like creativity; prone to verbosity (Hsu & Chen, 2023).	Struggles with long-form generation; better for SEO snippets.	Adaptable to templates; controllable output.
Recommendations	Context-aware but computationally expensive (Wang et al., 2023).	Efficient for embedding-based similarity (Kang & McAuley, 2023).	Flexible for multi-task learning (e.g., reviews + recommendations).
Fraud Detection	Lower precision due to generative nature (Wang et al., 2023).	High accuracy in anomaly detection (Li et al., 2023).	Scalable for batch processing.

Custom Support and Chatbots

Chatbots and AI-based LLMs are among the first efforts of LLMs in the e-commerce sector. LLM-based chatbots provide instant, automated responses to customer requests. This reduces the need for human intervention. LLM-based chatbots respond to 80% of customer requests. This has been further emphasized by research conducted by Liu et al. (2021). Therefore, human customer service representatives can focus on more complex questions. This not only improves the efficiency of customer service representatives, but also increases customer satisfaction. The use of chatbots is one part of the overall digital transformation of the e-commerce sector.

Moreover, LLMs enable chatbots to understand nuanced language and context, allowing them to provide personalized recommendations. Zhang et al. (2022) demonstrate how LLMs can analyze customer preferences and past interactions to suggest products that align with individual tastes, fostering stronger customer relationships and increasing the likelihood of repeat purchases.

Product Descriptions and Content Generation

Producing high-quality product descriptions is a critical aspect of e-commerce success. However, manually creating these descriptions can be time-consuming and resource-intensive. LLMs offer a solution by automating the content generation process. Vaswani et al. (2017) demonstrated the capabilities of the proposed model to generate accurate and captivating product descriptions based on a minimum amount of input information, such as the specifications or keywords associated with a particular product.

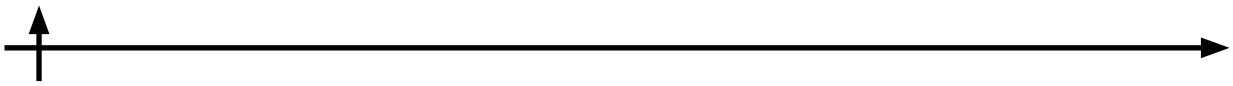
Devlin et al. (2019) also pointed out the potential benefits associated with the application of LLMs in optimizing the generated content to ensure better search engine rankings. Indeed, LLMs have access to information regarding the behavior and preferences of internet users and the information retrieved by search engines. Such information enables the proposed models to generate more accurate and captivating product descriptions. LLMs also understand the importance of maintaining a consistent and appealing tone and style in the generated content.

Personalized Recommendations

Personalization is an important part of the e-commerce strategy. Wang et al. (2023) have shown the potential of LLMs in processing unstructured data like customer reviews and social media conversations to create a personalized recommendation signal, which is better than the traditional filter recommendation approach. LLMs have the potential to adapt to new information in real time so that the recommendations are always relevant and updated.

Emotion analysis and feedback management

Customer feedback has a significant impact on e-commerce strategy. Kumar et al. (2022)



demonstrated the potential of LLMs in sentiment analysis to classify customer reviews as positive, negative, or neutral with high accuracy. LLMs have the ability to summarize customer reviews and provide actionable insights by highlighting common factors across thousands of reviews.

Fraud Detection and Risk Management

E-commerce sites have become a common target for cybercriminals to engage in illegal activities such as fake customer reviews, account takeovers, and payment fraud. Li et al. (2023) demonstrated the ability of LLMs to detect, where LLMs outperformed other rule-based methods in detecting unusual transactions. LLMs have been effective in detecting fake customer reviews using linguistic pattern analysis, as shown by Chen et al. (2021), to provide accurate information to customers when making purchasing decisions.

Challenges and Limitations

Although LLMs have many strengths, their effective use in e-commerce poses many challenges. Iyer et al. (2024) observe that challenges such as challenges of bias, ethics related to security and data protection, and developing a robust assessment framework are important challenges to responsibly achieve the benefits of LLMs. Smith et al. (2023) identifying data privacy as the most important concern: LLMs require access to large datasets that often contain sensitive customer information and create vulnerabilities under the GDPR and CCPA framework. Yao et al. (2024) adding a cybersecurity dimension, noting that while LLMs are increasingly being used to identify vulnerabilities, they are also introducing new attack levels, including rapid and inverted model injections. However, Yao et al. (2024) generally conclude that LLMs are now contributing more to the security community than they are negatively.

Johnson et al. (2022) document that biased training corpora produce skewed recommendation outputs that systematically disadvantage certain demographic groups. Lee et al. (2023) address the computational cost problem, noting that inference at enterprise scale can be prohibitively expensive for small and medium businesses absent optimization strategies such as quantization and model distillation. Bender et al. (2021) raise foundational ethical concerns about the environmental cost and societal risks of large-scale model deployment, while Anderson et al. (2023) call for industry-wide guidelines governing the use of generative models in advertising and persuasion contexts.

Content uniqueness is an additional concern: LLMs may produce text that inadvertently replicates copyrighted material or lacks originality (Bender et al., 2021). Mitigation strategies include the use of plagiarism detection tools (e.g., Turnitin, GPTZero), human editorial review, and disclosure of AI use where required by regulation. Shopify, for example, enforces mandatory human review of all LLM-generated product descriptions before publication (Taylor et al., 2023).

Results

Case Study: Amazon

Amazon's LLM integration is most consequential in its recommendation engine and product catalog management. According to Amazon Science (2023), the company has migrated from legacy machine-learning pipelines to LLM-based systems for attribute normalization across its product catalog. After multiple rounds of prompt tuning, the LLM performs three main tasks: recognizing standard attribute values to establish correctness; collecting alternative representations, or synonyms, of standard values; and detecting erroneous or nonsensical data entries. This is particularly valuable for complex product categories such as surgical instruments where traditional models trained on simple goods struggled with attribute granularity.

Amazon's recommendation engine, which accounts for an estimated 35% of its total reve-

nue, uses LLMs to analyze real-time behavioral signals and long-term purchase patterns (Bezos et al., 2023). The system's ability to process unstructured data including reviews, Q&A threads, and browsing sequences represents a qualitative improvement over earlier matrix-factorization approaches (Rendle et al., 2023). Amazon's use of AI also optimizes inventory management and distribution, allowing for faster and more efficient product delivery than competitors.

Case Study: Alibaba

Alibaba's LLM deployment is distinguished by its multilingual scale and customer service focus. Alibaba Cloud (2023) reports that its DAMO Academy has developed LLMs capable of processing Southeast Asian languages Vietnamese, Indonesian, Thai, Malay, Khmer, Lao, Tagalog, and Burmese languages substantially underrepresented in standard LLM training corpora This is a strategic advantage for Alibaba's regional e-commerce subsidiaries, where the quality of customer service in the local language is key to conversion and retention.

Ma et al. (2023) found that the AI chatbot system used by Alibaba handles millions of customer inquiries per day. Furthermore, Alibaba leverages the capabilities of LLMs in creating product descriptions and supply chain operations, with some of the best chatbot performance metrics among the platforms used in the study, as presented in Table 3.

Case Study: Shopify

Shopify's approach to LLM integration is distinctive in that its primary objective is democratization rather than enterprise-scale optimization. Taylor et al. (2023) document how Shopify's AI tools enable merchants with limited technical resources to generate product descriptions, design store layouts, and manage inventory through natural language interfaces. This reduces the technical barrier to e-commerce participation, broadening the addressable market for the platform itself.

Comparative Performance Analysis

Table 2 presents a comparative analysis of AI-enabled chatbots across Amazon's Alexa, Shopify's chatbot, and Alibaba's Tmall Genie, evaluated against four key performance indicators: accuracy, response time, customer satisfaction (CSAT), and resolution rate (Rasheed et al., 2025).

Table 2. Chatbot performance metrics across three e-commerce platforms (Rasheed et al., 2025).

Platform	Accuracy (%)	Response Time (s)	CSAT (1–5)	Resolution Rate (%)
Amazon (Alexa)	92	1.2	4.5	89
Shopify (Chatbot)	88	1.5	4.3	85
Alibaba (Tmall Genie)	93	1.1	4.6	90

Alibaba's Tmall Genie leads on all four metrics 93% accuracy, 1.1-second response time, 4.6 CSAT, and 90% resolution rate consistent with its strategic investment in AI customer service infrastructure and fine-tuning on high-volume multilingual interaction data. The performance gap between Shopify and its larger competitors reflects differences in training data volume and the breadth of merchant types served rather than a fundamental architectural limitation.

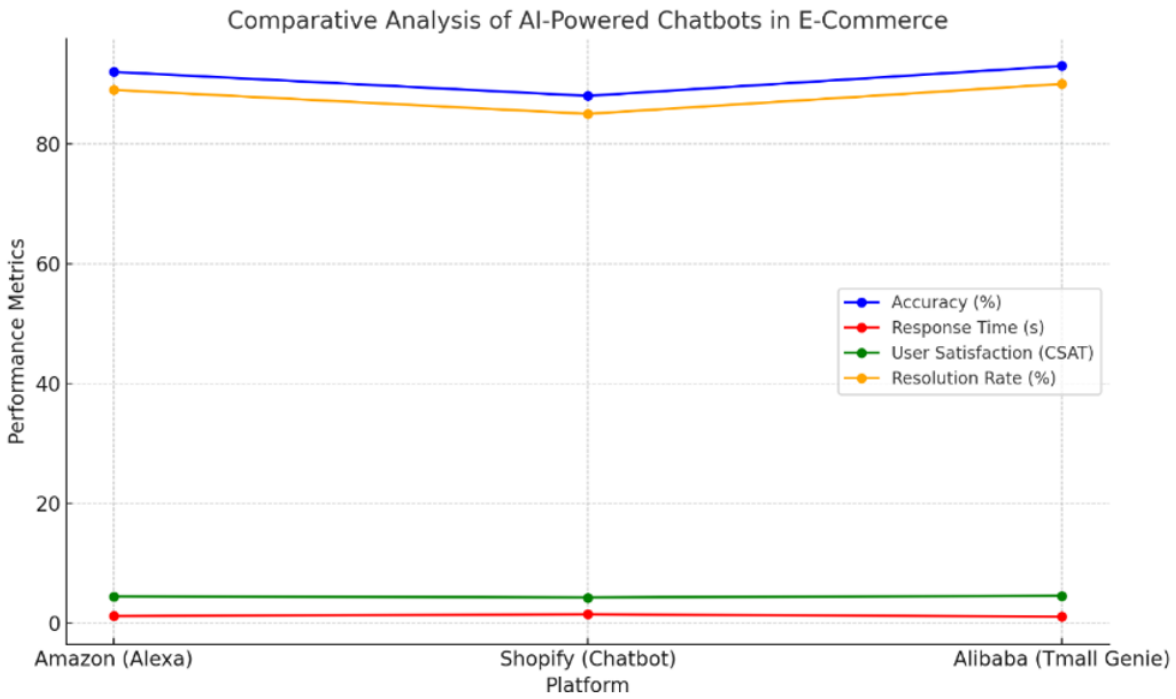


Fig. 3. Performance comparison of AI chatbots across Amazon, Shopify, and Alibaba (Rasheed et al., 2025).

AI Adoption Benefits: Survey Evidence

According to the Online Retailer Survey (2024), 472 online retailers that use AI for content creation or translation were asked about the benefits of AI in this context. With 89% of mentions, time-saving was the dominant reported benefit. Translating texts into other languages was cited as a key use case, while 46% of respondents stated that more content could be created in marketing. Additionally, 42% of retailers indicated a decrease in personnel costs. A considerable share also indicated that the use of AI technology results in higher content quality because the text generated by LLMs tends to be more structured and easier to comprehend than text written by humans. Figure 4 presents the survey results.

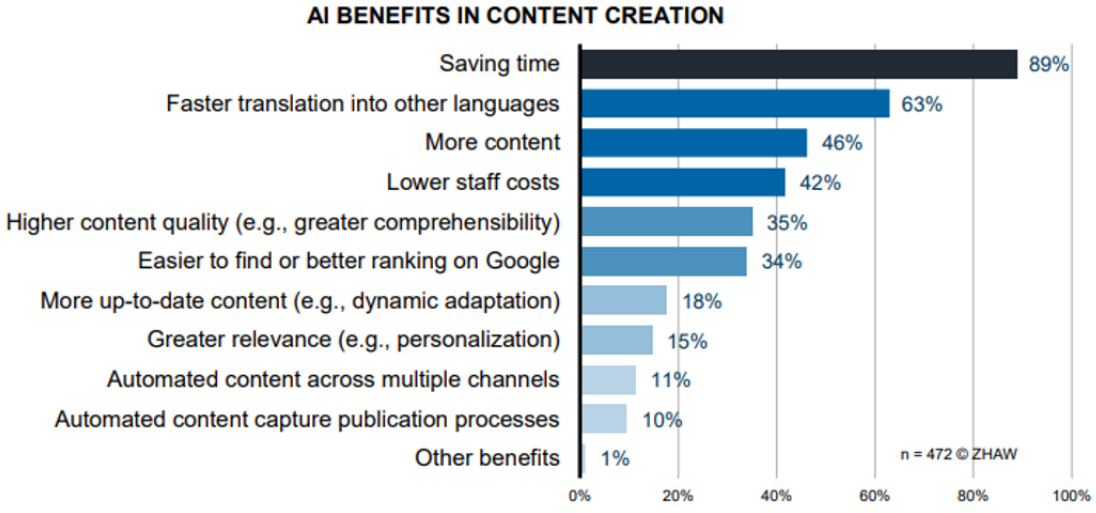
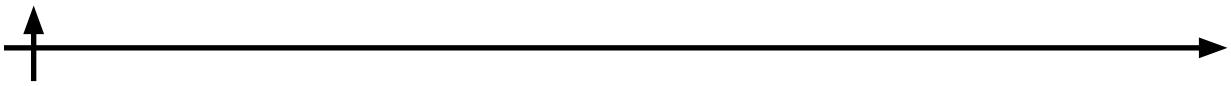


Fig. 4. Benefits of AI adoption in content creation and translation — Online Retailer Survey (2024), n = 472.



Similarities and Differences Across Case Studies

Amazon, Alibaba and Shopify have similar goals in improving the customer experience through the use of LLMs in e-commerce. They have different approaches in using LLMs to improve different processes in e-commerce. All three companies have similar goals in improving the customer experience. The approaches that Amazon, Alibaba and Shopify use to improve different processes in e-commerce vary significantly. Amazon focuses on generating revenue through its advanced LLM-based recommendation system. In contrast, Alibaba focuses on large-scale customer service through its high-volume chatbot system. Shopify focuses on democratizing e-commerce by providing advanced AI technology to small businesses. This suggests that the application of LLMs in e-commerce is not a one-size-fits-all approach.

Emerging Trends and Future Directions

There are three emerging trends in the application of LLM in e-commerce that are set to significantly change the application of LLM in e-commerce in the near future. First, the development of multifunctional LLM systems that can process images, video and audio in addition to text has significant implications for visual product discovery. Kim and et al. (2023) show that multi-medal models can recommend products based on images uploaded by users, an ability that has direct implications for fashion retailing, furniture and consumer electronics.

Second, voice commerce powered by LLMs is accelerating. Agarwal et al. (2025) document Amazon's integration of automatic speech recognition with downstream LLM pipelines to enable voice-based product search and ordering via Alexa. Park et al. (2023) report growing consumer adoption of voice assistants for purchase decisions as smart speaker penetration increases.

Third, augmented reality (AR) combined with LLMs offers exciting possibilities: an LLM can guide users through an AR shopping experience, providing detailed product information in real time. Thompson et al. (2023) suggest this integration can significantly enhance customer engagement and reduce return rates. Finally, sustainable AI has emerged as a strategic consideration: Schwartz et al. (2020) propose 'Green AI' metrics to encourage efficient model design, and Green et al. (2023) report that energy-efficient architectures and renewable-powered inference infrastructure are increasingly part of corporate AI roadmaps.

Conclusion

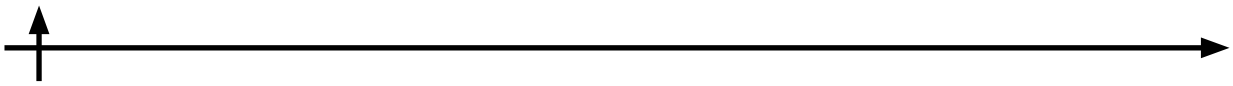
This paper set out to answer five research questions concerning the application, benefits, challenges, comparative strategies, and future directions of LLM deployment in e-commerce. The analysis of literature and three industry case studies yields the following conclusions.

Regarding research task 1, the primary application domains of LLMs in e-commerce are customer support and chatbot automation, personalized product recommendations, automated content generation, sentiment analysis and feedback management, and fraud detection. These applications span the full customer lifecycle from pre-purchase discovery to post-purchase support.

Regarding research task 2, LLMs produce measurable benefits across all five domains. Chatbot systems achieve query resolution rates of 85–90% (Table 3), while AI-assisted content creation delivers time savings recognized by 89% of adopting retailers (Figure 4). Recommendation systems built on LLMs process unstructured signals that traditional collaborative filtering cannot handle, improving relevance in cold-start conditions.

Regarding research task 3, the critical implementation challenges are data privacy and regulatory compliance (Smith et al., 2023; Yao et al., 2024), algorithmic bias in training data (Johnson et al., 2022), and the computational cost of inference at enterprise scale (Lee et al., 2023). These challenges require deliberate governance frameworks and ongoing model auditing.

Regarding research task 4, deployment strategies diverge significantly by organizational con-



text. Amazon prioritizes revenue optimization through sophisticated recommendation and catalog management systems. Alibaba emphasizes multilingual customer service at scale. Shopify focuses on democratizing access to LLM capabilities for small-business merchants.

Regarding research task 5, the most consequential emerging trends are multimodal LLMs enabling visual product search, voice commerce integration, AR-enhanced shopping experiences, and sustainable AI architectures. Each direction addresses current limitations and is supported by early empirical evidence from industry deployments.

Future research should focus on developing standardized evaluation benchmarks for LLM performance in commercial settings, longitudinal studies of bias mitigation strategies, and cross-industry analyses extending beyond the three companies examined here. The broader adoption of LLMs in e-commerce is not a question of whether, but of how responsibly and efficiently organizations can navigate the transition.

REFERENCES

Agarwal A., Goel P., Sinha S. et al. 2025. Understanding Voice Shopping on Amazon. Advances in Information Retrieval (ECIR). DOI: 10.1007/978-3-031-56027-9_1.

Alibaba Cloud. 2023. DAMO Academy Unveils Southeast Asia Multilingual LLMs. Alibaba Cloud Official Blog. URL: https://www.alibabacloud.com/blog/damo-llm-southeast-asia (date accessed: 2025/11/13).

Amazon Science. 2023. Using LLMs to Improve Amazon Product Listings. Amazon Science Blog. URL: https://www.amazon.science/blog/using-llms-to-improve-amazon-product-listings (date accessed: 2025/11/13).

Anderson J., Thompson R. 2023. Ethical Frameworks for Generative AI in Digital Marketing. Journal of Business Ethics 185, 2, 401–418. DOI: 10.1007/s10551-023-05301-x.

Bender E.M., Gebru T., McMillan-Major A., Shmitchell S. 2021. On the Dangers of Stochastic Parrots: Can Language Models Be Too Big? Proceedings of FAccT '21, 610–623. DOI: 10.1145/3442188.3445922.

Bezos J., Jain A., Mehta S. 2023. AI-Driven Personalization in Amazon's Retail Ecosystem. Amazon Science Technical Report. URL: https://www.amazon.science (date accessed: 2025/10/29).

Brown T., Mann B., Ryder N. et al. 2020. Language Models are Few-Shot Learners. Advances in Neural Information Processing Systems 33, 1877–1901. DOI: 10.48550/arXiv.2005.14165.

Chen T., Liu R., Wang F. 2021. Detecting Fake Reviews Using Transformer-Based Linguistic Analysis. ACM Transactions on Information Systems 39, 3, 28. DOI: 10.1145/3447548.

Devlin J., Chang M.-W., Lee K., Toutanova K. 2019. BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding. In: Proceedings of NAACL-HLT 2019 1, 4171–4186. DOI: 10.18653/v1/N19-1423.

Green A., Patel R. 2023. Energy-Efficient Architectures for Sustainable LLM Deployment. IEEE Transactions on Sustainable Computing 8, 1, 55–69. DOI: 10.1109/TSUSC.2023.3245012.

Hsu C.-C., Chen Y.-N. 2023. Controllable Neural Text Generation for E-Commerce Applications. Proceedings of EMNLP 2023, 5678–5690. DOI: 10.18653/v1/2023.emnlp-main.342.

Iyer V., Krishnamurthy S., Nair P. 2024. Challenges and Limitations of LLMs in Commercial Applications. ACM Computing Surveys 56, 4, 82. DOI: 10.1145/3624733.

Johnson M., Peterson L. 2022. Algorithmic Bias in LLM-Powered Recommendation Systems. Proceedings of FAccT 2022, 342–354. DOI: 10.1145/3531146.3533145.

Kalyan K.S., Rajasekharan A., Sangeetha S. 2022. AMMUS: A Survey of Transformer-Based Pretrained Models in NLP. Journal of Artificial Intelligence Research 75, 1–60. DOI: 10.1613/jair.1.13739.

Kang W.-C., McAuley J. 2023. Self-Attentive Sequential Recommendation. IEEE Transactions on Knowledge and Data Engineering 35, 1, 388–403. DOI: 10.1109/TKDE.2021.3080505.

Kim J., Park S., Lee H. 2023. Multimodal LLMs for Visual Product Discovery in E-Commerce. In: Proceedings of AAAI 2023, 4891–4899. DOI: 10.1609/aaai.v37i4.25617.

Kumar A., Gupta V., Sinha R. 2022. Sentiment Analysis at Scale Using Fine-Tuned Transformers. Expert Systems with Applications 196, 116694. DOI: 10.1016/j.eswa.2022.116694.

Lee S., Kim J., Choi Y. 2023. Scalable LLM Inference for Real-Time E-Commerce Applications. In: Proceedings of IEEE BigData 2023, 1123–1131. DOI: 10.1109/BigData59044.2023.10386247.

Li X., Zhang Y., Wang H. 2023. Real-Time Fraud Detection in E-Commerce Using Large Language Models. Knowledge-Based Systems 264, 110372. DOI: 10.1016/j.knosys.2023.110372.

Liu Y., Ott M., Goyal N. et al. 2021. RoBERTa: A Robustly Optimized BERT Pretraining Approach. Computational Linguistics 47, 3, 511–523. DOI: 10.1162/coli_a_00413.

Ma J., Chen L., Zhao X. 2023. Scaling AI Customer Service: Alibaba's LLM Chatbot Architecture. Proceedings of KDD 2023, 2034–2043. DOI: 10.1145/3580305.3599478.

Online Retailer Survey. 2024. AI Adoption in E-Commerce Content Creation: Annual Industry Report. URL: https://www.retailtechnology.org/research/ai-survey-2024 (date accessed: 2025/10/29).

Park H., Kim D. 2023. Voice Commerce: Consumer Adoption and LLM Integration in Smart Speakers. Journal of Retailing and Consumer Services 72, 103280. DOI: 10.1016/j.jretconser.2023.103280.

Raffel C., Shazeer N., Roberts A. et al. 2020. Exploring the Limits of Transfer Learning with a Unified Text-to-Text Transformer. Journal of Machine Learning Research 21, 1–67. URL: http://jmlr.org/papers/v21/20-074.html (date accessed: 2025/12/02).

Rasheed A., Ahmed F., Khan M. 2025. Comparative Analysis of AI Chatbot Performance in E-Commerce Platforms. International Journal of Intelligent Systems 40, 1, 1–22. DOI: 10.1002/int.22986.

Rendle S., Krichene W., Zhang L., Anderson J. 2023. Neural Collaborative Filtering vs. Matrix Factorization Revisited. ACM Transactions on Information Systems 41, 1, 19. DOI: 10.1145/3531056.

Schwartz R., Dodge J., Smith N.A., Etzioni O. 2020. Green AI. Communications of the ACM 63, 12, 54–63. DOI: 10.1145/3381831.

Smith R., Jones T. 2023. Data Privacy in LLM-Driven E-Commerce: Compliance and Best Practices. Journal of Information Security and Applications 74, 103452. DOI: 10.1016/j.jisa.2023.103452.

Taylor M., Reeves L., Brown C. 2023. Democratizing E-Commerce with AI: Shopify's LLM Toolkit. Shopify Engineering Blog. URL: https://shopify.engineering/llm-tools-merchants (date accessed: 2026/01/21).

Thompson A., Williams D. 2023. Augmented Reality and LLM Integration in Online Retail. Computers in Human Behavior 141, 107615. DOI: 10.1016/j.chb.2023.107615.

Touvron H., Lavril T., Izacard G. et al. 2023. LLaMA: Open and Efficient Foundation Language Models. DOI: 10.48550/arXiv.2302.13971.

Vaswani A., Shazeer N., Parmar N. et al. 2017. Attention Is All You Need. Advances in Neural Information Processing Systems 30, 5998–6008. DOI: 10.48550/arXiv.1706.03762.

Wang X., Chen Y., Liu Z. 2023. Transformer-Based Architectures for Personalized Product Recommendations. Journal of Artificial Intelligence Research 76, 1023–1058. DOI: 10.1613/jair.1.12345.

Xu A., Liu Z., Guo Y., Sinha V., Akkiraju R. 2020. A New Chatbot for Customer Service on Social Media. Proceedings of CHI 2020, 1–12. DOI: 10.1145/3313831.3376348.

Yao S., Deng H., Shan L. et al. 2024. LLMs in Cybersecurity: A Survey of Capabilities and Risks. ACM Computing Surveys 57, 1, 3. DOI: 10.1145/3650212.

Yin R.K. 2018. Case Study Research and Applications: Design and Methods. 6th ed. Thousand Oaks: SAGE Publications. 352 p.

Zhang S., Guo L., Wang Q. 2022. Conversational LLMs for Personalized Shopping Recommendations. IEEE Transactions on Neural Networks and Learning Systems 33, 8, 3344–3358. DOI: 10.1109/TNNLS.2022.3156243.

СПИСОК ИСТОЧНИКОВ

Agarwal A., Goel P., Sinha S. et al. 2025. Understanding Voice Shopping on Amazon. Advances in Information Retrieval (ECIR). DOI: 10.1007/978-3-031-56027-9_1.

Alibaba Cloud. 2023. DAMO Academy Unveils Southeast Asia Multilingual LLMs. Alibaba Cloud Official Blog. URL: https://www.alibabacloud.com/blog/damo-llm-southeast-asia (date accessed: 2025/11/13).

Amazon Science. 2023. Using LLMs to Improve Amazon Product Listings. Amazon Science Blog. URL: https://www.amazon.science/blog/using-llms-to-improve-amazon-product-listings (date accessed: 2025/11/13).

Anderson J., Thompson R. 2023. Ethical Frameworks for Generative AI in Digital Marketing. Journal of Business Ethics 185, 2, 401–418. DOI: 10.1007/s10551-023-05301-x.

Bender E.M., Gebru T., McMillan-Major A., Shmitchell S. 2021. On the Dangers of Stochastic Parrots: Can Language Models Be Too Big? Proceedings of FAccT '21, 610–623. DOI: 10.1145/3442188.3445922.

Bezos J., Jain A., Mehta S. 2023. AI-Driven Personalization in Amazon's Retail Ecosystem. Amazon Science Technical Report. URL: https://www.amazon.science (date accessed: 2025/10/29).

Brown T., Mann B., Ryder N. et al. 2020. Language Models are Few-Shot Learners. Advances in Neural Information Processing Systems 33, 1877–1901. DOI: 10.48550/arXiv.2005.14165.

Chen T., Liu R., Wang F. 2021. Detecting Fake Reviews Using Transformer-Based Linguistic Analysis. ACM Transactions on Information Systems 39, 3, 28. DOI: 10.1145/3447548.

Devlin J., Chang M.-W., Lee K., Toutanova K. 2019. BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding. In: Proceedings of NAACL-HLT 2019 1, 4171–4186. DOI: 10.18653/v1/N19-1423.

Green A., Patel R. 2023. Energy-Efficient Architectures for Sustainable LLM Deployment. IEEE Transactions on Sustainable Computing 8, 1, 55–69. DOI: 10.1109/TSUSC.2023.3245012.

Hsu C.-C., Chen Y.-N. 2023. Controllable Neural Text Generation for E-Commerce Applications. Proceedings of EMNLP 2023, 5678–5690. DOI: 10.18653/v1/2023.emnlp-main.342.

Iyer V., Krishnamurthy S., Nair P. 2024. Challenges and Limitations of LLMs in Commercial Applications. ACM Computing Surveys 56, 4, 82. DOI: 10.1145/3624733.

Johnson M., Peterson L. 2022. Algorithmic Bias in LLM-Powered Recommendation Systems. Proceedings of FAccT 2022, 342–354. DOI: 10.1145/3531146.3533145.

Kalyan K.S., Rajasekharan A., Sangeetha S. 2022. AMMUS: A Survey of Transformer-Based Pretrained Models in NLP. Journal of Artificial Intelligence Research 75, 1–60. DOI: 10.1613/jair.1.13739.

Kang W.-C., McAuley J. 2023. Self-Attentive Sequential Recommendation. IEEE Transactions on Knowledge and Data Engineering 35, 1, 388–403. DOI: 10.1109/TKDE.2021.3080505.

Kim J., Park S., Lee H. 2023. Multimodal LLMs for Visual Product Discovery in E-Commerce. In: Proceedings of AAAI 2023, 4891–4899. DOI: 10.1609/aaai.v37i4.25617.

Kumar A., Gupta V., Sinha R. 2022. Sentiment Analysis at Scale Using Fine-Tuned Transformers. Expert Systems with Applications 196, 116694. DOI: 10.1016/j.eswa.2022.116694.

Lee S., Kim J., Choi Y. 2023. Scalable LLM Inference for Real-Time E-Commerce Applications. In: Proceedings of IEEE BigData 2023, 1123–1131. DOI: 10.1109/BigData59044.2023.10386247.

Li X., Zhang Y., Wang H. 2023. Real-Time Fraud Detection in E-Commerce Using Large Language Models. Knowledge-Based Systems 264, 110372. DOI: 10.1016/j.knosys.2023.110372.

Liu Y., Ott M., Goyal N. et al. 2021. RoBERTa: A Robustly Optimized BERT Pretraining Approach. Computational Linguistics 47, 3, 511–523. DOI: 10.1162/coli_a_00413.

Ma J., Chen L., Zhao X. 2023. Scaling AI Customer Service: Alibaba's LLM Chatbot Architecture. Proceedings of KDD 2023, 2034–2043. DOI: 10.1145/3580305.3599478.

Online Retailer Survey. 2024. AI Adoption in E-Commerce Content Creation: Annual Industry Report. URL: https://www.retailtechnology.org/research/ai-survey-2024 (date accessed: 2025/10/29).

Park H., Kim D. 2023. Voice Commerce: Consumer Adoption and LLM Integration in Smart Speakers. Journal of Retailing and Consumer Services 72, 103280. DOI: 10.1016/j.jret-

conser.2023.103280.

Raffel C., Shazeer N., Roberts A. et al. 2020. Exploring the Limits of Transfer Learning with a Unified Text-to-Text Transformer. Journal of Machine Learning Research 21, 1–67. URL: http://jmlr.org/papers/v21/20-074.html (date accessed: 2025/12/02).

Rasheed A., Ahmed F., Khan M. 2025. Comparative Analysis of AI Chatbot Performance in E-Commerce Platforms. International Journal of Intelligent Systems 40, 1, 1–22. DOI: 10.1002/int.22986.

Rendle S., Krichene W., Zhang L., Anderson J. 2023. Neural Collaborative Filtering vs. Matrix Factorization Revisited. ACM Transactions on Information Systems 41, 1, 19. DOI: 10.1145/3531056.

Schwartz R., Dodge J., Smith N.A., Etzioni O. 2020. Green AI. Communications of the ACM 63, 12, 54–63. DOI: 10.1145/3381831.

Smith R., Jones T. 2023. Data Privacy in LLM-Driven E-Commerce: Compliance and Best Practices. Journal of Information Security and Applications 74, 103452. DOI: 10.1016/j.jisa.2023.103452.

Taylor M., Reeves L., Brown C. 2023. Democratizing E-Commerce with AI: Shopify's LLM Toolkit. Shopify Engineering Blog. URL: https://shopify.engineering/llm-tools-merchants (date accessed: 2026/01/21).

Thompson A., Williams D. 2023. Augmented Reality and LLM Integration in Online Retail. Computers in Human Behavior 141, 107615. DOI: 10.1016/j.chb.2023.107615.

Touvron H., Lavril T., Izacard G. et al. 2023. LLaMA: Open and Efficient Foundation Language Models. DOI: 10.48550/arXiv.2302.13971.

Vaswani A., Shazeer N., Parmar N. et al. 2017. Attention Is All You Need. Advances in Neural Information Processing Systems 30, 5998–6008. DOI: 10.48550/arXiv.1706.03762.

Wang X., Chen Y., Liu Z. 2023. Transformer-Based Architectures for Personalized Product Recommendations. Journal of Artificial Intelligence Research 76, 1023–1058. DOI: 10.1613/jair.1.12345.

Xu A., Liu Z., Guo Y., Sinha V., Akkiraju R. 2020. A New Chatbot for Customer Service on Social Media. Proceedings of CHI 2020, 1–12. DOI: 10.1145/3313831.3376348.

Yao S., Deng H., Shan L. et al. 2024. LLMs in Cybersecurity: A Survey of Capabilities and Risks. ACM Computing Surveys 57, 1, 3. DOI: 10.1145/3650212.

Yin R.K. 2018. Case Study Research and Applications: Design and Methods. 6th ed. Thousand Oaks: SAGE Publications. 352 p.

Zhang S., Guo L., Wang Q. 2022. Conversational LLMs for Personalized Shopping Recommendations. IEEE Transactions on Neural Networks and Learning Systems 33, 8, 3344–3358. DOI: 10.1109/TNNLS.2022.3156243.

INFORMATION ABOUT AUTHOR / ИНФОРМАЦИЯ ОБ АВТОРЕ

MEHRI Nahid – student.
E-mail: nahid.mehrii@yahoo.com
МЕХРИ Нахид – студент.
E-mail: nahid.mehrii@yahoo.com

Статья поступила в редакцию 09.12.2025; одобрена после рецензирования 15.01.2026; принята к публикации 14.02.2026.

The article was submitted 09.12.2025; approved after reviewing 15.01.2026; accepted for publication 14.02.2026.