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Research Article

A Systematic Literature Review on AI and NLP Applications for Customer Support Automation and Digital Service

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Abstract. This study presents a Systematic Literature Review on Artificial Intelligence (AI) and Natural Language Processing (NLP) applications for customer support automation and digital service optimization. The review follows the PRISMA framework to ensure methodological rigor and transparency, focusing on literature published between 2020 and 2025 from the Scopus database. The findings reveal that AI-driven technologies, including Machine Learning, Deep Learning, and Large Language Models, have significantly improved efficiency, response time, and customer satisfaction in customer support and digital service. Common NLP applications include sentiment analysis, ticket classification, and automated response generation. Among these, hybrid and transformer-based models demonstrate superior accuracy and contextual understanding compared to traditional algorithms. However, several challenges persist, including data quality limitations, privacy and security concerns, algorithmic bias, and linguistic ambiguities such as sarcasm and negation. Moreover, issues related to trust and ethical adoption continue to influence user acceptance of AI systems. This review provides a comprehensive synthesis of current methodologies, trends, and research gaps, offering insights for future studies to develop explainable, secure, and human-centered AI systems that enhance the sustainability and transparency of digital customer support services.

Keywords: Artificial Intelligence; Customer Support Optimization; Natural Language Processing; Text Classification; User Satisfaction Analysis.

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1. Introduction

Customer support is vital for an organization's reputation, profitability, and customer retention. Their effectiveness relies on processes, technology, and personnel. Integrating technology with well-structured processes strengthens customer relationships and aligns operations with strategic goals (Mabotja & Mkhomazi, 2024). Traditionally, customer support has relied heavily on human agents to handle inquiries, resolve issues, and guide customers through various processes. However, the growing complexity and volume of customer interactions, coupled with the demand for rapid response times, have driven the adoption of automation technologies. In service management, automation plays a crucial role in the classification and prioritization of support tickets. In conventional systems, incoming service requests are manually categorized and prioritized by human agents based on urgency, complexity, and available resources. While this approach can be effective to some extent, it is often time-consuming and prone to human error, particularly when ticket volumes are high (Peddinti et al., 2023). Traditional customer service systems are often associated with long waiting times and inflexible working hours, leading to customer dissatisfaction. To overcome these limitations, the implementation of chatbots in customer service has emerged as an effective solution, enabling real-time responses and continuous support. Currently, chatbots are employed across various departments, with the customer support sector accounting for approximately 37% of chatbot applications. Whether addressing information requests, complaints, or service inquiries such as returns and exchanges, chatbot-based systems provide 24/7 assistance, allowing customers to receive personalized responses within seconds (Misischia et al., 2022).

The adoption of Artificial Intelligence (AI) and Natural Language Processing (NLP) thus represents a strategic priority for the evolution of customer support. AI has fundamentally transformed customer service, beginning with basic NLP capabilities, such as the early dialogue program ELIZA in 1966, which simulated human conversation and laid the groundwork for future customer service applications. Substantial advancements in NLP during the 1990s allowed machines to better comprehend and generate human language, a crucial development for creating intuitive customer service interfaces. This evolution was further propelled by the emergence of Machine Learning (ML) in the 1980s and subsequently Deep Learning (DL) in the 2010s, leading to advanced AI systems like Apple's Siri (2011) and IBM's Watson (2011). These systems were capable of handling complex interactions through enhanced speech recognition. Most recently, the early 2020s introduced Large Language Models (LLMs) , which leverage deep learning to produce text resembling human writing and understand contextual clues , significantly improving the coherence and personalization of AI-based chatbots and resulting in more natural and engaging customer service interactions (Sai Mounika Inavolu, 2024).

Given the complexity of contact center automation and the rapid advancements in NLP and Deep Learning, there is a clear need to review and synthesize existing research. Previous studies have explored NLP applications in customer support automation, often positioning themselves as early efforts in this area. Through systematic mapping, this Systematic Literature Review (SLR) aims to help researchers and practitioners identify current research gaps, address ongoing challenges, and outline directions for developing intelligent customer support systems in the future (Gamboa-Cruzado et al., 2022). This study aims to fill the gap in previous literature reviews by providing a comprehensive synthesis of AI and NLP applications in customer support automation, emphasizing hybrid model development, data security, and linguistic complexity.

The research framework also encompasses key aspects such as current AI development trends, the evolution of ML and DL into hybrid models, their real-world implementations, and related challenges, including AI's impact on human behavior. Accordingly, this SLR examines the methodologies of NLP, ML, and DL in automating customer support functions. The review analyzes data processing techniques, model comparisons, and domain-specific applications to deepen understanding of current progress and identify future research opportunities.

2. Research Methodology

This study employs a Systematic Literature Review (SLR) to explore how AI and NLP can be utilized in contact center systems to facilitate user complaint handling. The SLR method was chosen for its ability to provide a structured, comprehensive, and transparent review of relevant scientific research. The review process follows the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) for Search Strategies framework proposed by (Page et al., 2021) which has been adapted for literature studies in the field of information systems, aligning with the focus of this research. The overall SLR activities are summarized in Figure 1.

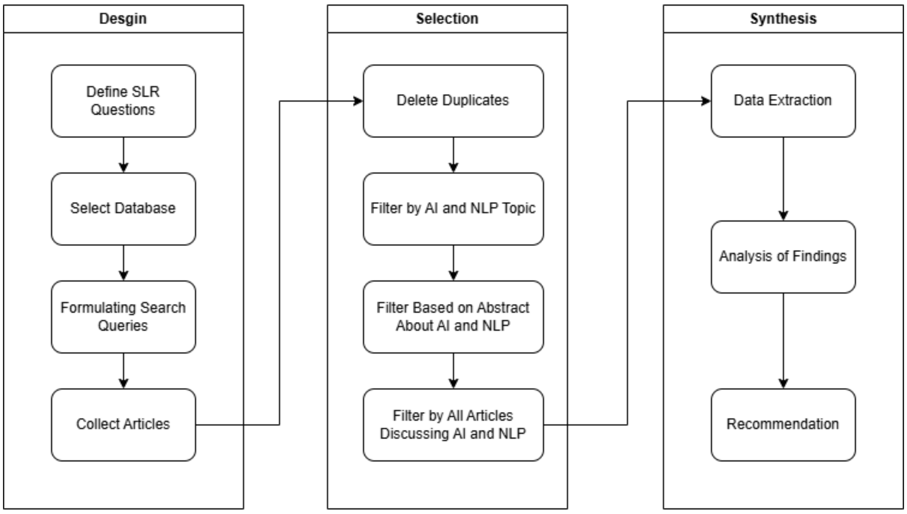

Figure 1. SLR Process.

Figure 1 illustrates that the SLR process consists of three main stages: design, selection, and synthesis. In the design stage, the researcher formulates research questions, identifies relevant databases, and develops search keywords to obtain appropriate publications. The collected search results are then compiled as preliminary study material. The selection stage ensures the relevance of the articles to the topics of NLP and AI through processes such as duplicate removal, topic-based screening, and abstract review, resulting in a final set of articles explicitly addressing NLP and AI. The synthesis stage involves data extraction and analysis from the selected studies to identify key findings that form the foundation for developing the conceptual model or architecture of this research. This structured, transparent, and replicable approach enhances the validity and reliability of the review outcomes.

SLR Design

In the initial stage, the research requirements were defined to ensure that the article selection process aligns with the study's objectives. These requirements include formulating the research questions for the SLR, selecting appropriate scientific databases for article retrieval, developing search keywords, and establishing inclusion and exclusion criteria. The main goal of this SLR is to identify AI trends in customer support and the challenges encountered in its development. Accordingly, to guide the information extraction process from the reviewed literature, the sub-research questions of this SLR are formulated as follows.

RQ1: How does the implementation of AI based systems and chatbots influence customer satisfaction (CSAT) and productivity performance across various sectors such as banking, e-commerce, and customer support services?

RQ2: How do different ML, DL, and LLM techniques such as SVM, BERT, LSTM, and others compare in performance for specific NLP tasks relevant to customer support, including ticket classification, sentiment analysis, and resolution time prediction?

RQ3: What are the main challenges and recurring research gaps identified in the literature regarding the implementation and data management of AI and NLP systems for customer service and software engineering, particularly those related to data integrity and user data security?

This study employs Scopus (https://www.scopus.com/) as the primary database, as it is recognized as one of the leading scientific databases providing access to high-quality, up-to-date, and relevant publications in the fields of information technology, information systems, and software architecture development. The selection of Scopus is based on its broad multidisciplinary coverage and strong indexing of topics such as NLP, AI, and Machine Learning. Utilizing this database is expected to yield a comprehensive and representative body of literature to support the analysis and synthesis processes in this research.

The keyword search in this study was conducted using the following Scopus query: TITLE-ABS-KEY (("ticket classification" OR "IT Helpdesk" OR "Customer Support") AND ("natural language processing" OR "machine learning" OR "artificial intelligence" OR "deep learning")) AND (LIMIT-TO (OA, "all")). The Scopus search was conducted once on October 1, 2025, at 09:25. Filters were applied to include only open-access publications published between 2020 and 2025, limited to journal articles and conference papers. The inclusion criteria for this study required that all selected documents be written in English, consequently, documents in other languages were excluded from consideration. Duplicate records and papers without full-text availability were excluded. The search process was documented using a PRISMA flowchart to ensure transparency in article selection. This strategy was designed to obtain high-quality, current, and thematically relevant literature to support the research objectives.

SLR Process Selection

The article selection process in this study was conducted systematically to ensure that only relevant and high-quality literature was included for further analysis. The selection procedure consisted of five main stages, as illustrated in Figure 2.

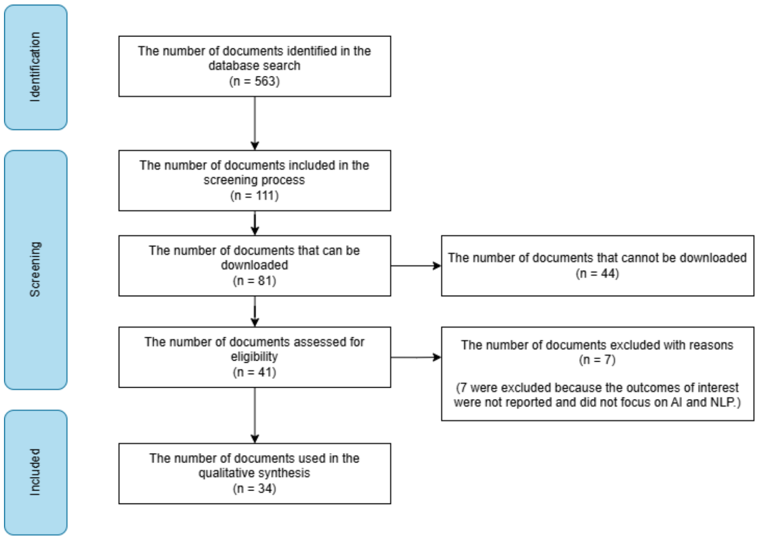

Figure 2. Selection Procedure Stages.

As illustrated in Figure 2, the selection process began with a total of 563 articles retrieved from the database search. After the screening stage, the number was reduced to 111 documents, of which 81 were available for download. Subsequently, 7 articles were excluded because they did not focus on AI or NLP. Consequently, a total of 34 documents were selected for the final analysis. Figure 3 shows the distribution of article data by year.

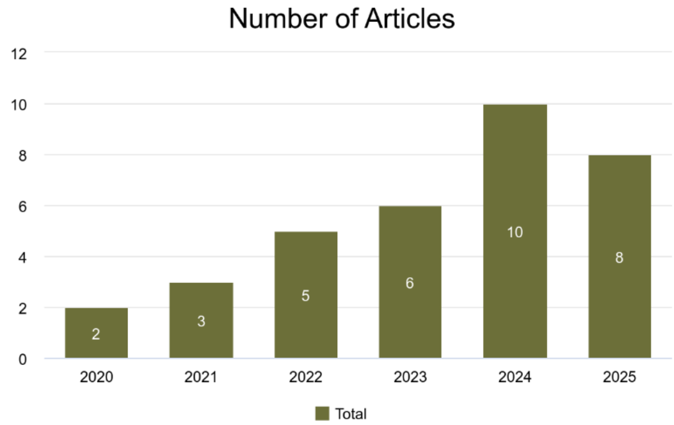

Figure 3. Number of Articles.

Figure 3 shows an increase in research related to AI and NLP from 2020 to 2025, while Figure 4 illustrates the types of articles selected, consisting of journal articles and conference papers, based on the sources obtained from Scopus, journal articles tend to dominate compared to conference papers.

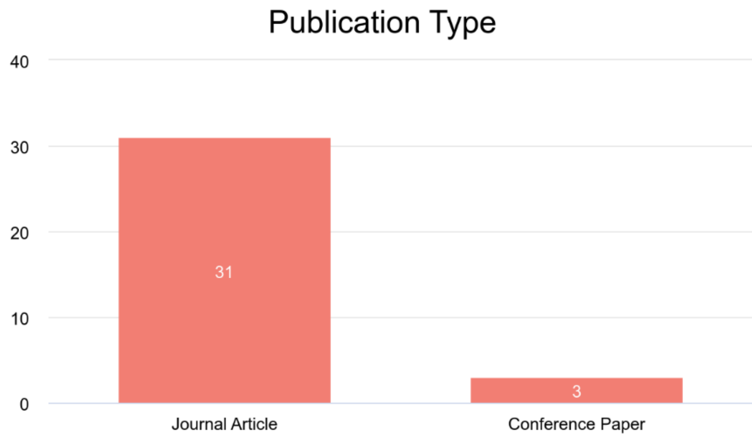

Figure 4. Publication Type.

Data Synthesis

After completing the article selection process and extracting relevant data, the next stage involved synthesizing the findings from the selected literature. The synthesis aimed to identify patterns, trends, research gaps, and common architectural components used in the development of digital-based service systems, particularly those adopting AI and NLP approaches. Each article was analyzed thematically and categorized based on its research focus, technological approach, and contribution to the advancement of customer support systems. The extracted information was then organized into Table 1 to facilitate data grouping and conclusion drawing. The synthesis results serve as the foundation for developing recommendations on the design and improvement of NLP-based customer support systems.

Table 1: Data synthesis grouping

No.	Data Extraction	Description	Type
1	AI Trends	This includes an analysis of the latest developments in the field of Artificial Intelligence (AI), encompassing advancements in model capabilities, emerging machine learning approaches, and current research trends that are gaining prominence.	General
2	AI Application Implementation	It highlights how AI is applied across various sectors such as education, healthcare, industry, and public services and examines its impact on efficiency and innovation.	General
3	Behavior and Perception	It describes how individuals and organizations perceive, respond to, and adapt to AI technologies, including issues related to trust, ethics, and social acceptance.	RQ1
4	ML/DL Algorithm Tuning	It focuses on optimization techniques in machine learning and deep learning models aimed at enhancing the accuracy and overall performance of AI systems.	RQ2

5	AI Challenges	It encompasses various challenges, including data limitations, model complexity, algorithmic bias risks, and ongoing concerns regarding security and privacy in AI development.	RQ3
6	Further Research	Subsequent research is directed toward the development of tourism villages in Indonesia.	General

3. Results And Discussion

After conducting data synthesis and identification, the authors proposed several findings derived from the extracted data related to the implementation of AI and NLP in customer support and contact center systems.

This section presents the results and discussion, beginning with trends in AI adoption. (Prakash, 2025) introduced *OptiMediaAI*, a video-based communication system that provides immersive and personalized interactions, addressing the monotony of traditional channels such as phone, email, and chat. (Medeiros et al., 2023) developed an AI-powered chatbot integrating Optical Character Recognition (OCR) and NLP to help users quickly extract information from vehicle manuals. In the financial sector, (Pokamestov & Nikitin, 2024) emphasized AI's strategic role in enhancing decision-making and operational efficiency within Russian banks. (Rajendran, 2023) highlighted that AI-driven automation and influencer collaboration improve brand visibility and customer service, while Voice Search Optimization (VSO) enhances accessibility in digital marketing.

(Tsaiyi et al., 2025) proposed an AI-based fashion recommendation system that personalizes shopping experiences based on user preferences, and (Kondybayeva et al., 2024) explored generative AI voice chatbots capable of human-like responses, marking a step toward natural human–AI communication. (Treacy, 2022) observed AI's growing role in speech, image, and text recognition, automation, and fraud detection, while (Olujimi & Ade-Ibijola, 2023) noted its value in managing large-scale social media interactions. In the context of Industry 4.0, (Treacy, 2022) and (Mhlanga, 2020) underscored AI's contribution to financial inclusion, particularly through big data analytics enabling unsecured lending for underserved populations. Collectively, these studies demonstrate AI's pervasive integration across communication, banking, marketing, and retail, transforming both operational models and user experiences.

Concerning human behavior and perception (RQ1), (Ahmed et al., 2023) found that early detection of negative sentiment improves customer issue resolution. (Alawaji & Aloraini, 2025) reported that sentiment analysis enhances digital banking support quality, while (Pukach et al., 2025) observed AI's role in optimizing ticket handling. (Akdemir & Bulut, 2024) revealed increasing trust in chatbots, with most users engaging repeatedly each year. (Rajendran, 2023) and (Poorna Chandran & Tholath, 2025) further confirmed AI's behavioral and service personalization impacts, although age influences adoption. From a socio-economic view, (Mhlanga, 2020) linked AI to digital financial inclusion for low-income groups, and (Aliwy et al., 2022) highlighted its potential in security, governance, and public welfare. Overall, human perception of AI remains shaped by trust, accessibility, and ethical considerations, even as AI continues to enhance efficiency and satisfaction.

Emerging AI trends highlight generative voice interaction, OCR-based virtual assistants, and sentiment-driven automation across industries. Yet, these innovations remain underexplored in educational service contexts, particularly in automated ticket classification, multilingual support, and adaptive communication systems. Future studies should extend these AI applications to academic environments to enhance service efficiency and engagement within educational institutions.

Based on various research findings discussing current algorithmic developments, Table 2 presents the results proposed by researchers for advancing AI and NLP applications in customer support and contact center systems. Table 2 corresponds to RQ2, which focuses on algorithm tuning and optimization.

Table 2. Research Findings on Algorithm (RQ2).

Category	Authors	Accuracy of Algorithm
Machine Learning	(Priya et al., 2021)	Bi-LSTM: 99.05% with a loss of 0.0347. LSTM: 98.4% with a loss of 0.046.
	(Ahmed et al., 2023)	Decision Trees and Bagging 0.75 and F-measure 0.75. Initial Features 0.68 and F-measure 0.68, achieved by Decision Trees using CCF + CAF features. Sentiment analysis tool (Stanford API) 89%.
	(Prakash, 2025)	Training and Validation achieved 95%. Training and Validation Loss was 1.42%.
	(Almeida et al., 2024)	Balanced class parameter, the predictive ability for the negative class increased from 59% to 74%.
	(Tai et al., 2025)	RF 70.04%, followed by DT 66.34% and XGBoost 64.76%.
	(Borg et al., 2021)	SVM 0.831, LSTM 0.93.
	(Bruni et al., 2023)	SVM 74.53%.
	(Powell et al., 2020)	SVM (confidence interval threshold) 95%, estimated 69.9% of the fields are filled (populated) by the algorithm with an accuracy of 94.5%.
	(Haw et al., 2022)	Resolution Time Prediction (RTP) using RF with Attention, recording a Test RMSE of 341,463 seconds (≈3 days 22 hours), while the NN model showed a Test RMSE of 717,631 seconds (≈8 days 7 hours).
	(Aliwy et al., 2022)	LSTM 0.875, SVM 0.833, MaxEnt 0.852
	(Alawaji & Aloraini, 2025)	Voting Classifier with (class weighting) with 90.24% Accuracy and 90.20% F1 Score. SVM without class weighting (90.45%), but the class-weighted Voting Classifier outperforms it overall.

	(Papadia et al., 2022)	Topic Modeling (LDA + CGS/VB) Collapsed Variational Bayes (cvb0) for best performance.
	(Zafar, 2023)	Bag of Words (BOW). Predicted probability is very high, such as intent 'search' with probability 0.99999213.
Deep Learning	(Korade et al., 2024)	CNN 0.825 and XGBoost 0.813.
	(Bruni et al., 2023)	CNN 89.72%.
	(Medeiros et al., 2023)	LLM. High accuracy for Ask your PDF than Question and Answer System.
	(Alawaji & Aloraini, 2025)	DT has the lowest accuracy of 86.47% with class weighting than LSTM, LLM (Few-shot): GPT 4 Accuracy 82.76% (F1 82.33%). SILMA (Accuracy 81.11%). The LLM (Zero-shot): GPT 4 model is the best with Accuracy 79.78%.
	(Leonova & Zuters, 2021), (Leonova & Zuters, 2022)	Non-lexical features (NLME) and bag-of-words representation prediction accuracy 49%
Hybrid Algorithm	(Waiker et al., 2025)	Autoencoder-LSTM Hibrida optimized by ACO-WOA achieved 94.12% accuracy for the audio dataset and 95.94% for the image dataset. ML Perceptron achieved 56% accuracy, CNN 72% accuracy, BiLSTM 85% accuracy, and TCN 87% accuracy on the audio dataset. On the image dataset, this model outperformed SVM 87.76% accuracy, DSAE 89% accuracy, and FD-CNN 94% accuracy.
	(Singh Ruprah et al., 2024)	BERT and *Reinforcement Learning* (BERT-RL). BLEU and ROUGE scores are higher compared to traditional RNN-based models (such as LSTM and GRU) and CNN
	(Oleiwi et al., 2025)	CNN and MFCC for feature extraction; BiLSTM for classification; NCA (Neighborhood Component Analysis) for optimal feature selection 97.02% accuracy.
	(Al-Mutawa & Al-Aama, 2024)	EDL (Ensemble-based Deep Learning) high accuracy than ML.

Table 2 shows that various ML and DL algorithms remain widely adopted in text classification research, with several studies experimenting with hybrid models and, more recently, transformer-based architectures such as BERT and large language models, though their application remains limited. Preprocessing techniques are consistently employed across studies, often involving data cleaning, normalization, and augmentation to ensure high-quality inputs. (Ahmed et al., 2023; Almeida et al., 2024; Papadia et al., 2022; Prakash, 2025) applied standard preprocessing steps, including the removal of URLs, usernames, hashtags, and emoticons, followed by lemmatization and grammatical tagging for linguistic consistency. Similarly, (Alawaji & Aloraini, 2025; Zafar, 2023) implemented tokenization, lemmatization, stop-word removal, and normalization to refine textual data. Hybrid model research by (Singh Ruprah et al., 2024; Waiker et al., 2025) also adopted comparable preprocessing workflows such as tokenization, lowercasing, and lemmatization to enhance data uniformity and model accuracy. Overall, most studies utilized core NLP operations such as tokenization, stemming, POS tagging, parsing, and semantic analysis, though detailed methodological descriptions were often limited. In its development, several challenges inevitably arise. Based on the results in Table 2 (RQ2), the most effective algorithms for future use are those that demonstrate high accuracy, adaptability, and contextual understanding. Deep learning models particularly Bi-LSTM, CNN, and transformer-based architectures such as BERT and GPT-4 consistently outperform traditional machine learning. Therefore, future research should prioritize hybrid architectures and transformer-based models to enhance prediction precision, contextual adaptability, and scalability in AI-driven customer support systems. Table 3 for answer RQ3 presents the findings from various studies that discuss the key challenges associated with the implementation of AI and NLP technologies.

Table 3. AI Challenges (RQ3).

Authors	Impact	Types of AI Challenges
(Jalali & Hongsong, 2024)	Chatbots improve business and industrial services.	Security and privacy issues, such as access control, data leakage during transmission, SQL injection attacks, and language model attacks.
(Korade et al., 2024)	Chatbot system can improve user experience and quickly meet user expectations.	High number of duplicate questions asked.
(Nuh et al., 2025)	AI has the potential to improve learning outcomes, encourage equitable access to technology, and foster more informed public discourse.	Largely due to the lack of regulations that guarantee the reliability of the system.
(Rajendran, 2023)	AI-driven Customer Support resulted in a 30% reduction in response time and a 15% increase in customer satisfaction scores.	Technical complexity, and data security concerns.
(Tsaiyi et al., 2025)	AI has generally been shown to significantly influence their purchase intentions towards products.	Concerns about product quality and suitability) and financial risk (fear of losing money).
(Poorna Chandran & Tholath, 2025)	Improve operational efficiency and customer service.	Financial loss, privacy issues, security, and inadequate user training.
(Puthukulangara et al., 2024)	Provide consistency of information through accurate responses.	In a non-deterministic approach, there is a risk of the chatbot generating potentially harmful responses (e.g., incorrect advice).
(Treacy, 2022)	AI will replace routine jobs.	AI has the potential to cause staffing levels to decrease and employee morale to decline.

(Mhlanga, 2020)	AI helps vulnerable groups, previously excluded due to risk concerns.	AI is highly dependent on the availability of quality data and the right quantity.
(Aliwy et al., 2022)	Predicting events such as election results or market trends.	Multi-polarity of words, Multi-polarity of text, Semantically ambiguous words, sarcasm.

RQ3 identifies several key challenges in the advancement of AI. (Jalali & Hongsong, 2024), (Rajendran, 2023), and (Poorna Chandran & Tholath, 2025) emphasized ongoing issues of data security and privacy. (Treacy, 2022) noted that AI adoption may lead to job displacement, while (Mhlanga, 2020) highlighted the dependence of AI systems on accurate and reliable data. (Aliwy et al., 2022) pointed out linguistic difficulties, such as multi-polarity of words, semantic ambiguity, and sarcasm, which complicate AI-based text analysis. (Puthukulangara et al., 2024) mentioned that chatbots can generate incorrect responses, reducing trust, and (Nuh et al., 2025) stressed the lack of regulatory frameworks to ensure data protection and ethical AI governance. To prevent potential losses and strengthen data security, organizations should adopt privacy-by-design principles, apply robust encryption, ensure model transparency, and establish strict data governance supported by continuous monitoring and regulatory compliance (Hakeemat Ijaiya, 2024; Joseph Nnaemeka Chukwunweike et al., 2024).

The existing research gap identified in this study lies in the limited exploration of comprehensive frameworks that integrate AI and NLP for secure, explainable, and context-aware customer support automation. While numerous studies demonstrate the effectiveness of Machine Learning, Deep Learning, and Large Language Models in enhancing response accuracy and customer satisfaction, challenges persist regarding data privacy, linguistic ambiguity, model interpretability, and user trust. Moreover, most current implementations remain domain-specific and lack adaptability across multilingual or cross-sector service environments. Future research should therefore focus on developing explainable AI (XAI) models that ensure transparency and fairness, strengthening data governance frameworks to protect user information, and advancing hybrid architectures capable of handling nuanced language understanding and it could be further refined, such as utilizing multilingual datasets and evaluating hybrid models within the educational helpdesk domain. Additionally, integrating human–AI collaboration mechanisms and emotion-aware systems could enhance personalization, empathy, and reliability in next-generation digital customer service platforms.

4. Conclusion

In conclusion, this study demonstrates that the integration of AI and NLP has significantly transformed digital customer support by improving efficiency, accuracy, and customer satisfaction. Through systematic analysis, it is evident that advanced models such as Deep Learning and Large Language Models outperform traditional machine learning in automating tasks like ticket classification and sentiment analysis. However, persistent issues particularly data security, privacy risks, linguistic complexity, and limited model transparency remain key obstacles to broader adoption. Therefore, future developments should prioritize explainable, secure, and human-centered AI frameworks to ensure trustworthy and adaptive customer service systems capable of sustaining long-term user engagement and organizational value.

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