iJRASET
International Journal For Research in Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 13 **Issue:** IX **Month of publication:** September 2025

DOI: https://doi.org/10.22214/ijraset.2025.74186

www.ijraset.com

Call: 08813907089 | E-mail ID: ijraset@gmail.com

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 13 Issue IX Sep 2025- Available at www.ijraset.com

Comprehensive Analysis of Chatbot Methods and Functions in Artificial Intelligence

Dr.Goldi Soni[1], Sambhavi Singh[2], Ansu Thakur[3]
[1]*Assistant Professor,* [2,3]*B.Tech CSE Amity University Chhattisgarh*

Abstract: ***Chatbots have long been a significant area of research. With their applications being more common across a variety of industries. These artificially intelligent conversational agents are made to mimic human communication through textual or audio means. From basic rule-based systems to sophisticated AI-driven apps that can comprehend, interpret, and react to intricate user inquiries, chatbot technology has significantly evolved over time. The creation and integration of numerous fundamental technologies that improve the chatbot's usability, flexibility, and functionality have been the main drivers of this advancement.***

The main technologies that have influenced the chatbot landscape are thoroughly reviewed in this paper. It presents the five main technologies—natural language processing (NLP), pattern matching, semantic web, data mining, and context-aware computing—that are essential to the creation of contemporary chatbots. Natural language processing (NLP) has revolutionized human communication and machine learning by allowing chatbots to comprehend and produce human language. Advanced language models enable chatbots to process user input more precisely and contextually, producing responses that are more accurate and pertinent. Despite being an earlier method, pattern matching has developed alongside machine learning techniques to enable chatbots to identify patterns in user input, continuously enhance their responses, and offer a more customized experience for consumers.

Keywords: Chatbot, Semantic Web, Data Mining, Pattern Recognition, Natural Language Processing, Natural Language Understanding, Natural Language Generation, and Text-Aware Computing.

I. INTRODUCTION

Artificial intelligence (AI) systems have recently been developed by computers to offer services that are human-friendly and based on human comprehension [1]. These AI systems' primary technology is language intelligence, which enables users to interact with one another and access information without being constrained by language barriers. Additionally, because instant messaging-based social networking services are so convenient, mobile messengers are already combining sophisticated systems that offer more than just messaging capabilities.

Chatbots are one of the language-intelligence technologies that are now gaining a lot of interest in both academic and real-world contexts. A non-human virtual conversation robot that can respond to customer inquiries is known as a chatbot [2]. Users can quickly get the information they need by sending messages to the chatbot services without having to visit websites or launch apps. As a result, numerous businesses are presently using chatbots to provide a range of services to their clients as part of their advertising and company marketing efforts [3,4]. Because there are many kinds of chatbots using different approaches, it is vital to research the features of chatbots to increase their conversational maturity and carry out more pertinent interactions with them.

Enabling machines to speak natural language to people is one of the fundamental problems of chatbots. In 1950, Alan Tune introduced the basic concept of a chatbot, and in 1966, the ELIZA mimicked human conversation. But this has exposed constraints that appear to be intelligent. By expanding the ELIZA system later in 1995, ELIZA attempted to create a discourse pattern using the AI markup language (AIML); yet its shortcomings remain apparent. Jabberwacky was a trailblazer in the field of voice-based systems in text-based systems in 1988. This was one of the earliest attempts to build AI through human interaction. Recently, chatbots have integrated AI technology so that they can comprehend context and react when a user asks questions or gives commands in a human language correspondingly. Since deep learning technology is used in this case as the discussions mount up, a foundation has been established to increase accuracy via self-education.

In terms of natural language processing (NLP), natural language understanding (NLU), and natural language generating (NLG), chatbots are now researching this crucial topic. Additionally, chatbots are examining a variety of technologies, including the semantic web, data, and pattern recognition. Mining and computers are sensitive to context. The millennial generation's preference for messaging apps and the development of AI-related technology are fueling the chatbot industry's expansion.

At the moment, Facebook Messenger and WhatsApp hold the largest market shares worldwide, while WeChat and LINE hold the same shares in China and Japan, respectively. According to many users, mobile messaging apps are anticipated to develop into messaging platforms rather than just communication apps thanks to chatbot services.

In the future, it might also develop into a medium- and long-term growth engine. The app- focused mobile marketplaces will be subsumed into chatbot platforms if AI-based chatbots proliferate quickly. Additionally, it's possible that the Companies' current customer counseling centers may be replaced with automated interactive chatbot platforms that are accessible from anywhere at any time. Furthermore, it is anticipated that chatbots will develop into consulting firms with knowledge in industries like law, medicine, and finance. Additionally, as deep learning technology advances, current businesses, public services, online-to-offline (O2O) models, and personal assistant systems—such as intelligent personal assistants, or IPAs, will be integrated with new technologies to increase their reliance on chatbots.

The primary goals of these chatbot studies are to determine how well chatbots comprehend user messages and how well they can respond with pertinent information. Numerous researchers continue to investigate methods to accomplish these final objectives; hence, a variety of chatbots have been created using complex techniques. Chatbots will be actively used in the future to raise customer happiness in every aspect of daily life. This document is organized as follows. In Section 2, the methods for creating chatbots are examined, and the available research is reviewed. The fields in which chatbot research is being used are introduced in Section 3. Future directions are outlined in Section 4, which brings the paper to a close.

II. LITERATURE REVIEW

Artificial Intelligence (AI) has improved automation, efficiency, and user engagement, which has drastically changed customer service. The literature on AI-powered chatbots explores their evolution, technological advancements, and implementation challenges.

Abiagom and Ijomah (2024) examined the role of AI in customer service, highlighting key technologies such as Natural Language Processing (NLP), chatbots, and speech recognition. They emphasized that AI-driven interactions enhance customer satisfaction by offering personalized and real-time responses. However, challenges such as data quality, privacy concerns, and system integration need to be addressed.

Amballa (2023) discussed AI-powered customer care technologies such as chatbots, email automation, and IVR call automation. His research emphasized that AI improves service delivery by reducing response times and optimizing human resource allocation. His findings indicate that AI-driven triage mechanisms prioritize critical customer queries, routing them to human agents for resolution.

Suta et al. (2020) explored machine learning approaches in chatbots, concluding that NLP remains a key factor in chatbot efficiency. The study highlighted advancements in sentiment analysis, intent recognition, and automatic response generation, which contribute to improved human-like interactions.

Sai Abitha (2021) categorized chatbots based on their architecture, interaction style, and industry applications. She analyzed chatbot implementation in sectors like healthcare, education, and customer service, emphasizing their ability to handle repetitive tasks efficiently.

The integration of AI chatbots faces several challenges, including algorithmic bias, data privacy issues, and user acceptance. Future research should focus on improving chatbot personalization, enhancing contextual understanding, and addressing ethical concerns associated with AI deployment.

In the USA and the UK, Ekechi, Chukwurah, Oyeniyi, and Okeke (2024) evaluated user satisfaction with AI-driven chatbots across national borders. The study found that while chatbots improve customer service efficiency through quick response times and automated interactions, regional differences in language and cultural expectations affect user satisfaction. The research underscores the necessity of adapting chatbot technology to local user needs for optimal performance. Additionally, the study found that customers in the USA expect faster response times and greater personalization, whereas UK users value accuracy and politeness in chatbot interactions【16】.

Farhan Aslam (2023) looked at the most recent advancements in chatbot technology, such as deep learning, machine learning, and natural language processing (NLP).The study emphasizes how chatbots are becoming more prevalent in virtual assistants, emphasizing their ability to provide contextual understanding and personalized interactions. However, ethical concerns regarding privacy and AI bias remain critical challenges that need to be addressed. The study also discusses the limitations of NLP models in understanding nuanced customer queries and the importance of continuous learning for chatbots to enhance their adaptability【17】.

In 2019, Netra Pal Singh and Devender Singh looked into the employment of chatbots in Indian banks.Their research found that while banks have heavily invested in chatbot technology, their functionalities remain limited to handling predefined queries. The study suggests that greater AI integration and customer education are required to maximize chatbot efficiency in banking services. Additionally, the research highlights the reluctance of customers to fully trust AI-driven banking services due to concerns over data security and miscommunication
【18】.

Fatin Aqilah Binti Mohamad Roslan and Norliza Binti Ahmad (2023) analyzed how AI- powered voice assistants like Siri, Alexa, and Google Assistant have transformed customer service. These assistants enhance customer experience by providing real-time responses and personalized interactions. However, the study highlights growing concerns over data privacy and security, which need to be addressed to maintain consumer trust. The researchers also point out that user expectations have shifted, with a demand for more human-like conversational abilities in voice assistants【19】.Jessie Anderson (2024) investigated how AI chatbots affected CRM. The research found that chatbots have evolved from simple question-answering bots to intelligent virtual assistants capable of predictive analytics and multilingual adaptability. AI-driven automation in CRM has improved operational efficiency and customer engagement, although challenges such as chatbot misinterpretation and lack of human-like interactions persist. The study also suggests that businesses that effectively integrate chatbots into their CRM systems experience higher customer retention rates【20】.

In 2022, Monica Teodora Tudorache and Luminița Nicolescu carried out a thorough analysis of the literature regarding chatbots' function in customer support.Their study categorized customer experiences into chatbot-related, customer-related, and context-related factors, finding that response relevance and problem resolution are the most critical elements influencing user satisfaction. The research suggests that continuous AI training and updates are necessary for improved chatbot performance. Furthermore, their findings indicate that chatbots with enhanced emotional intelligence features can significantly improve customer interactions【21】.

Nidal Al Said, Dmitry Gura, and Dmitry Karlov (2022) assessed the effectiveness of AI-powered voice assistants in responding to user inquiries.The study found that while virtual assistants excel in structured tasks, they struggle with complex, open-ended queries. The research highlights the need for improved AI comprehension and adaptability for broader use cases. Additionally, the study suggests that voice assistants should be enhanced with multimodal capabilities to provide richer, more interactive user experiences【29】.

Nicolescu and Tudorache (2022) focused on user adoption trends and trust-building elements in their systematic literature review. Key findings suggest that chatbot anthropomorphism, conversational skills, and response accuracy play vital roles in customer engagement. Furthermore, the report emphasizes how customisation can boost client loyalty. The research also suggests that users are more likely to engage with chatbots that use humor, empathy, and context-awareness to create a more natural conversational flow【29】.

Another study examined the efficiency of AI-powered chatbots in smart devices. It found that while chatbots are effective in automating routine interactions, their limitations in understanding nuanced human emotions and complex requests remain a challenge. The study suggests that future chatbot development should focus on integrating emotional intelligence and advanced contextual learning. Moreover, the findings indicate that the integration of chatbots with IoT devices could enhance their usability in smart home environments【29】

III. APPLIED CHATBOT TECHNIQUES

A. Techniques Overview

Chatbots have evolved beyond their initial use in simple word-based interactions and are now being explored across diverse fields. This expansion has made it necessary to revisit and redefine key concepts in light of modern technological progress.

At the core of chatbot systems lies Natural Language Processing (NLP), which provides both a historical foundation and a technological framework. NLP is a central research domain in Artificial Intelligence (AI), enabling machines such as computers to analyze and work with human language. It can be divided into three specialized branches: NLP (processing), NLU (understanding), and NLG (generation).

NLP encompasses general techniques that process and extract information from text, making it useful in applications like chatbots, information retrieval, question answering, document classification, text clustering, machine translation, and intelligent agents.

NLU goes further by focusing on understanding the deeper semantics of natural language, handling complexities such as ambiguity and context.

NLG involves producing coherent, human-like language, making chatbot interactions more natural and engaging.

To move beyond basic language processing, next-generation chatbots must integrate multiple advanced technologies, including pattern recognition, semantic web frameworks, data mining, and context-aware computing.

Pattern recognition plays a crucial role in this integration. Within AI and cognitive science, it addresses the challenge of identifying and categorizing inputs such as sounds, text, or visual forms. In the context of chatbots, pattern recognition enables the classification of user queries into meaningful categories, enhancing the accuracy of responses.

The semantic web contributes by allowing machines to interpret not just the surface meaning of data but also the relationships between concepts. Unlike traditional web technologies that merely present information, the semantic web encodes knowledge in a structured, machine-readable format. For example, while the standard web may only display that "bananas are yellow," the semantic web can represent and reason about the conceptual relationship between "banana" and "yellow." This capability can make chatbots more intelligent by enabling them to conduct dialogues with a deeper contextual understanding.

Data mining is another powerful component, particularly when dealing with large-scale, unstructured data. By applying techniques such as association analysis, chatbots can identify frequently co-occurring phrases or questions, while regression analysis helps uncover relationships between dependent and independent variables. These methods allow chatbots to learn from historical interactions and generate more relevant and informed responses.

B. Natural Language Processing

Research in Natural Language Processing (NLP) has proposed system architectures designed to handle specific types of questions, as well as frameworks capable of generating diverse questions. Beyond chatbots, NLP technologies are widely applied across multiple domains of study. A key objective of many NLP-based studies is to facilitate ontology learning, where systems acquire structured knowledge representations from unstructured text.

Within NLP, Natural Language Understanding (NLU) is an area that has attracted significant attention. It has been applied in interactive agents, including those used in educational settings. Modern devices such as smartphones and tablets often require NLU engines to interpret user input, provide meaningful responses, and connect seamlessly with available applications. One practical approach in NLU involves using keyword extraction to explore the properties of text corpora and classify different types of texts. Other research has examined NLU specifically in the context of voice-based communication, emphasizing its role in enabling natural human–machine interaction.

Natural Language Generation (NLG), on the other hand, has evolved from producing very basic outputs to becoming a critical component in conversational systems. Key aspects of NLG include deciding when to generate responses, planning content, lexicalization, reference generation, sentence structuring, and surface realization of language. With advances in XML-based web technologies, recent studies have highlighted the importance of NLG in voice-enabled chatbot systems.

Traditionally, NLG relied heavily on template-based methods, where pre-designed frameworks dictated how responses were generated. While effective, these approaches often lacked flexibility. More recent work has introduced algorithmic methods to move beyond rigid templates, allowing for dynamic and context-aware responses. The growing reliance on voice recognition technologies has further accelerated NLG research, as conversational systems must now provide accurate, coherent, and contextually relevant replies to user speech.

C. Pattern Recognition

In chatbot systems, pattern recognition is often applied to identify and interpret user input once NLP techniques have been executed. This process enhances basic responses, making them more contextually accurate and capable of supporting tasks such as information retrieval, collaborative exchanges, and research-oriented conversations. In cases where advanced machine learning modules or complex NLP components such as syntactic and semantic analysis are absent, pattern recognition—particularly through AIML-based architectures—acts as a substitute. These AIML frameworks have been used to provide services across multiple programming environments and have proven useful in structuring responses within pattern analysis systems.

Pattern recognition in chatbots generally follows two distinct methodologies. The first employs a depth-first search algorithm, which requires substantial data resources for effective analysis. The second relies on keyword-driven grammar interpretation, where responses are generated by matching user input to predefined patterns. Both approaches contribute to improving the precision and adaptability of chatbot interactions.

D. Semantic Web

As the digital marketplace expands, one significant advancement is the emergence of the Semantic Web. The conventional World Wide Web hosts an immense volume of information, making it necessary to distinguish between older and contemporary terminology and to extract relevant insights from diverse sources. The Semantic Web addresses this challenge by transforming the traditional web into a network of meaning, where information is not only presented but also structured for intelligent processing.

At the core of this framework lies the concept of ontology. In philosophy, ontology refers to the study of being, including notions such as existence, reality, and the relationships between fundamental categories of entities. Rooted in metaphysics, it explores questions about what exists, how entities are organized, and how they can be classified or related within hierarchical structures.

In the context of the Semantic Web, ontology serves as a structured representation of knowledge that enables machines to interpret and connect information across different resources. This structured knowledge extraction is essential for developing new information retrieval tools capable of efficiently managing and interpreting the vast data available on the web.

E. Data Mining

Text mining has emerged as an advanced technology with notable commercial significance, as it provides in-depth analytical results rather than surface-level findings. Large-scale networked cluster systems are often employed to support extensive topical exploration, offering high levels of accessibility, adaptability, and efficiency. Despite these advances, certain aspects of data mining within chatbot applications remain insufficiently explored.

Data mining itself is a critical component of text mining, defined as the process of identifying patterns within large datasets. It combines methods from machine learning, statistics, and database management to reveal useful knowledge. With rapid progress in computing power, data storage, and connectivity, the volume of digital data has increased at an unprecedented rate. Consequently, data mining has established itself as a multidisciplinary field that plays an essential role in computer science.

The applications of data mining are widespread, spanning industries such as engineering, science, business, and government. Its growing importance reflects the recognition that extracting meaningful insights from data can create significant societal and economic value. This recognition has fueled demand not only for advanced data mining tools but also for skilled professionals capable of developing novel methodologies and applying them to real-world challenges. To meet this demand, academic and professional programs in data mining have been introduced worldwide, highlighting its status as a rapidly growing and impactful discipline.

F. Text-Aware Computing

In daily communication, people naturally adjust their voices depending on the environment—for instance, raising volume in noisy surroundings to ensure clarity or lowering it in formal settings like meetings to avoid disturbance. Similarly, text-aware computing seeks to adapt interactions by enabling systems to recognize and respond to context. Such technology allows computers to perform functions like presenting schedules or identifying individuals when required.

Beyond basic system comprehension, text-aware computing focuses on deeper capabilities such as interpreting contextual information and recognizing concepts within a given environment. Research in this area has explored its applications for restructuring contextual data, integrating advanced technologies, and strengthening security measures. These developments aim to improve the precision and reliability of context recognition, making text-aware computing a critical element in the evolution of intelligent systems.

G. Various Techniques

Human communication often changes according to the environment—voices are raised in noisy surroundings to ensure audibility, while in formal or quiet settings, people speak softly to avoid causing disturbance. In a similar way, text-aware computing is designed to adjust system responses based on contextual awareness. This technology enables computers to perform context-sensitive tasks such as displaying schedules or recognizing specific individuals when needed.

Unlike traditional systems that operate on predefined commands, text-aware computing emphasizes a deeper understanding of contextual information and the recognition of relevant concepts within an environment. Current research has investigated its potential for reorganizing contextual data, integrating cutting-edge technologies, and enhancing security frameworks. These advancements collectively contribute to achieving more accurate context recognition, positioning text-aware computing as a vital component in the advancement of intelligent and adaptive computing systems.

ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 13 Issue IX Sep 2025- Available at www.ijraset.com

IV. COMPARISON OF PAST PUBLISHED RESEARCH PAPER

With the increasing relevance of chatbots and AI-based conversational systems in healthcare, the five selected research studies provide a broad and insightful perspective on the topic. Abdul-Kader and Woods (2015) emphasize the technical aspects, presenting design frameworks and methodologies for chatbot development. In contrast, Dale (2016) adopts a wider lens by outlining the historical progression and conceptual foundations of chatbot evolution. Shum et al. (2018) focus specifically on social chatbots, highlighting their practical applications in healthcare-related communication. Deshpande et al. (2017) contribute by exploring deep learning approaches, AI architectures, and implementation strategies, which are crucial for building intelligent healthcare solutions. Finally, Berry (2004) addresses essential foundations in text mining, clustering, and classification, all of which underpin natural language processing techniques used in medical chatbots.

Together, these studies offer a balanced blend of theoretical insights, technical design principles, practical applications, advanced AI methods, and core NLP concepts. Their combined contributions make them highly valuable for understanding the role and potential of AI-driven chatbots in the healthcare sector.

Table-1 Comparison of past published research paper

S. No.	Authors & Year	Title	Key Focus	Strengths	Limitations	Comparison with Other Papers
1.	Dale, R. (2016)	"The Return of the Chatbots"	Provides an overview of chatbot evolution and AI-driven conversational agents.	Offers a historical perspective on chatbot development, evaluating key technological advancements.	Lacks in- depth technical details on chatbot frameworks.	More general than Abdul- Kader & Woods (2015), which focuses specifically on chatbot design methodologies.
2.	Abdul- Kader, S. A., & Woods, J. C. (2015)	"Survey on Chatbot Design Techniques in Speech Conversation Systems"	Explores different chatbot design approaches, including rule-based, pattern matching, and AI-driven chatbots.	Comprehensive analysis of chatbot development techniques, covering NLP and pattern recognition.	Does not extensively discuss deep learning and context-aware computing.	More technical than Dale (2016) but lacks future trend discussions like Shum et al. (2018).
3.	Shum, H. Y., He, X., & Li, D. (2018)	"From Eliza to XiaoIce: Challenges and Opportunities with Social Chatbots"	Examines the evolution of social chatbots, with a focus on Microsoft's XiaoIce.	Strong emphasis on real-world applications and chatbot performance in social settings.	Limited technical exploration of chatbot architectures.	More practical than Dale (2016) and Abdul-Kader & Woods (2015) but less technical than Deshpande et al. (2017).
4.	Deshpande, A., Shahane, A., Gadre, D., & Joshi, P. M. (2017)	"A Survey of Various Chatbot Implementation Techniques"	Provides a technical review of chatbot frameworks, AI models, and deep learning approaches.	thoroughly discusses statistical models, chatbot frameworks, AIML, and deep learning.	Limited focus on chatbot applications in business and industry.	More technical than Dale (2016) and Shum et al. (2018) but lacks industry application insights.

5.	Berry, M. W. (2004)	"Survey of Text Mining: Clustering, Classification, and Retrieval"	Discusses text mining techniques relevant to chatbot AI and NLP.	Provides an in-depth understanding of unsupervised learning, clustering, and classification for chatbots.	Focuses more on text mining techniques rather than chatbot-specific applications.	More foundational than Deshpande et al. (2017) but lacks chatbot-specific insights like Shum et al. (2018).

V. CONCLUSION

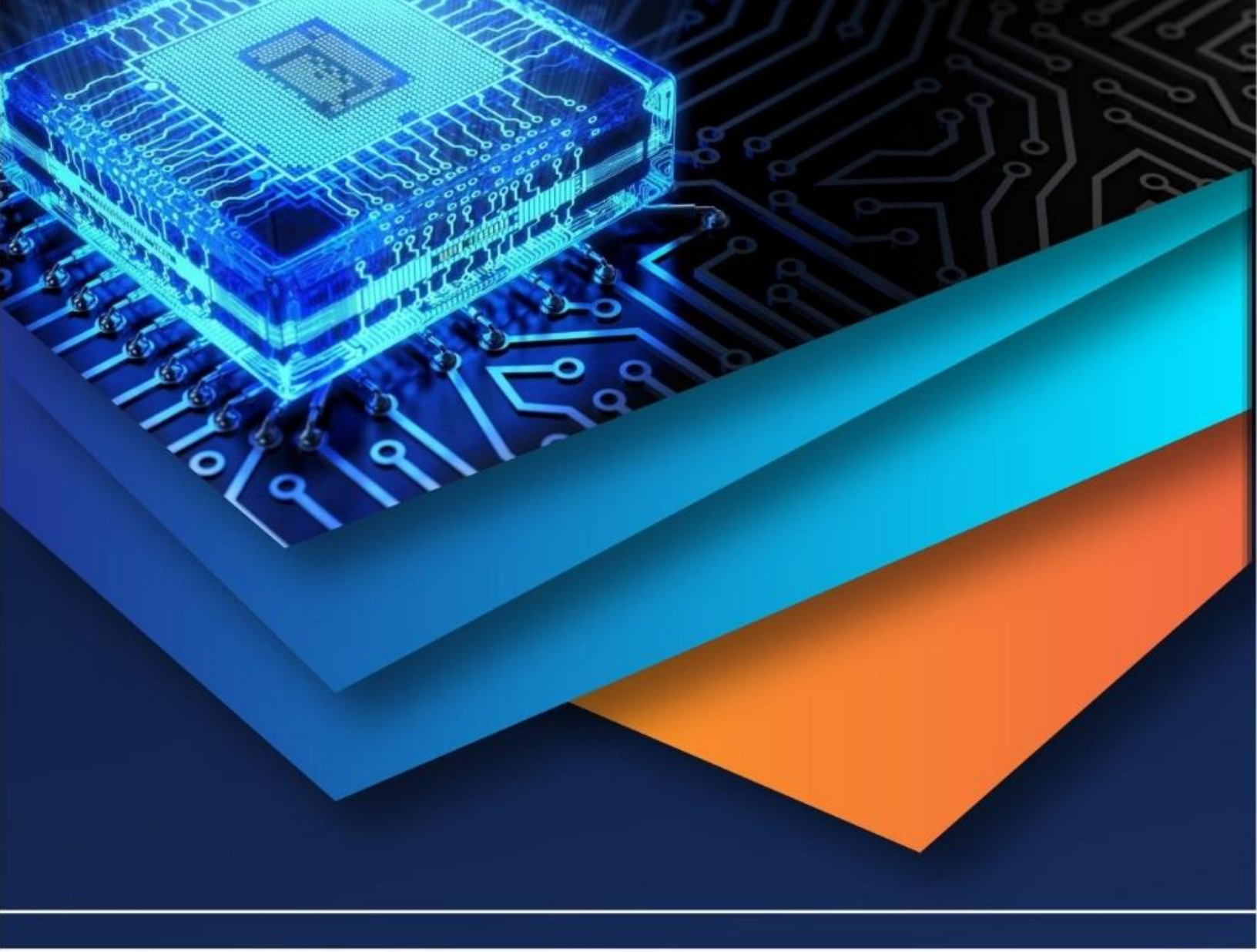
This research investigates the chatbot academic papers that have utilized the previously mentioned five technologies, categorizing them into five distinct groups. Regarding NLP or pattern recognition technology, numerous studies have been suggested since these technologies have been in use with chatbots for a significant duration. However, the implementation of relatively modern technologies such as data mining, situational computing, and semantic webs in chatbots has been relatively rare; as a result, these technologies were able to suggest a future line of inquiry. The chatbot industry is anticipated to expand rapidly in the coming years as a variety of chatbot products have been launched lately. Chatbots have boundless potential for advancement, and they are evolving to be more human-like than ever before. Notably, AI technologies significantly impact the enhancement of intelligence within chatbots. Moving forward, it is essential to explore ways to create chatbots that utilize voice command techniques that can be seamlessly integrated with them. Additionally, chatbot platform websites like "Chatfuel" offer APIs for developing similar voice command techniques. com," "Conversable. com," "Dialogflow. com," "Gupshup. io," "RASA. com," "Manuchat. com," "Danbee. ai," and "Playchat. ai." There are two main aspects in this area of research: the effectiveness of chatbots in understanding users' messages and their ability to deliver suitable responses in regard to context. Consider a situation where the chatbot is so sophisticated that users won't be able to tell if they are speaking with a chatbot or not. People will become accustomed to conversing with chatbots, and it will feel as natural as engaging with others, browsing the Internet, and viewing videos.

REFERENCES

[1] Artificial Intelligence: A Guide to Intelligent Systems, by M. Negnevitsky, 2nd ed.Harlow, UK: Pearson Education, 2005.
[2] A. Shevat, Designing Bots: Creating Conversational Experiences. Sebastopol, CA: O'Reilly Media, 2017.
[3] A. Zhou, M. Jia, and M. Yao, Business of Bots: How to Grow Your Company through Conversation. Ithaca, NY: Topbots Inc., 2017.
[4] M. McTear, Z. Callejas, and In the Conversational Interface, D. Griol discusses "Conversational interfaces: devices, wearables, virtual agents, and robots."Springer, Cham, Switzerland, 2016, pp. 283–308.
[5] Natural Language Engineering, vol. 22, no. 5, pp. 811-817, 2016; R. Dale, "The return of the chatbots."
[6] In the International Journal of Advanced Computer Science and Applications, "Survey on chatbot design techniques in speech conversation systems," volume 6, issue 7, pages 72–80, 2015, J. C. Woods and S. A. Abdul-Kader
[7] P. Pestanes and B. Gautier, "The rise of intelligent voice assistants: new gadget for your living room or window of opportunity to reshuffle the cards in the web economy?" 2017 [Online]. Available: https://www.wavestone.com/app/uploads/2017/09/Assistants-vocaux- ang-02-.pdf.
[8] A. Hotho, A. Nurnberger, and G. Paaß, "A brief survey of text mining," Ldv Forum, vol. 20, no. 1, pp. 19-62, 2015.
[9] "Applications of lexical information for algorithmically composing multiple-choice cloze items," with C. L. Liu, C. H. Wang, Z. M. Gao, and S. M. Huang, Proceedings of the 2nd Workshop on Building Educational Applications Using NLP, Ann Arbor, MI, 2015, pp. 1–8.
[10] A. Hoshino and H. Nakagawa, "A preliminary study on the creation of real-time multiple-choice questions for language testing," Proceedings of the 2nd Workshop on Building Educational Applications Using NLP, Ann Arbor, MI, 2005, pp. 17–20.
[11] "Arikiturri: an automatic question generator based on corpora and NLP techniques," Intelligent Tutoring Systems, I. Aldabe, M. L. De Lacalle, M. Maritxalar, E. Martinez, and L. Uria
[12] S. K. Shinde, V. Bhojane, and P. Mahajan, "NLP based object-oriented analysis and design from requirement specification," International Journal of Computer Applications, vol. 47, no. 21, pp. 30-34, 2012.
[13] D. Maynard, Y. Li, and W. Peters, "NLP techniques for term extraction and ontology population," in Ontology Learning and Population: Bridging the Gap between Text and Knowledge. Amsterdam, Netherlands: IOS Press, 2008, pp. 107-127.
[14] Ontology Learning and Population: Filling the Gap between Text and Knowledge, P. Buitel aar and P. Cimiano. IOS Press, Amsterdam, Netherlands, 2008.
[15] W. Ceusters, F. Buekens, G. De Moor, and A. Waagmeester, "The distinction between linguistic and conceptual semantics in medical terminology and its implication for NLP- based knowledge acquisition, Methods of Information in Medicine, vol. 37, no. 4-5, pp. 327- 333, 1998.
[16] In Advances in Web-Based Learning – ICWL 2005, S. M. Huang, C. L. Liu, and Z. M. Gao presented their work, "Computer-assisted item generation for listening cloze tests and dictation practice in English." Springer, Heidelberg, Germany, 2005, pp. 197–208.
[17] "Chatbot with common-sense database," M. Amilon, M.S. thesis, KTH Royal Institute of Technology, Stockholm, Sweden, 2015.
[18] T. Allen, R. Ellis, and M. Petridis, Applications and Innovations in Intelligent Systems XVI: Proceedings of AI-2008, the Twenty-Eighth SGAI International Conference on Innovative Techniques and Applications of Artificial Intelligence. London, UK: Springer, 2009.

[19] D. Feng, E. Shaw, J. Kim, and E. Hovy present "An intelligent discussion-bot for answering student queries in threaded discussions" in Proceedings of the 11th International Conference on Intelligent User Interfaces, Sydney, Australia, 2006, pp. 171–177.
[20] On October 1, 2014, M. Hebert filed U.S. Patent Application 14/503469, "NLU processing according to user-specified interests,"
[21] A. Horak, I. Kopecek, and K. Pala, Text, Speech and Dialogue. Heidelberg, Germany: Springer, 2012.
[22] In Proceedings of the ECAI workshop on Development and Evaluation of Robust Spoken Dialogue Systems for Real Applications, held in Riva del Garda, Italy in 2006, S. Varges and M. Purver discuss "Robust language analysis and generation for spoken dialogue systems."
[23] "Using semantic classification trees to understand natural language," by R. Kuhn and R. De Mori, IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 17, no. 5, 1995, pp. 449–460
[24] "Developing applied natural language generation systems," by E. Reiter and R. Dale, Natural Language Engineering, vol. 3, no. 1, pp. 57-87, 1997.
[25] In Proceedings of the 10th Conference on European Chapter of the Association for Computational Linguistics, Stroudsburg, PA, 2003, pp. 247-250, G. Wilcock discusses "Integrating natural language generation with XML web technology."
[26] O. Rambow, S. Bangalore, and "Natural language generation in dialog systems," papers by M. Walker, Proceedings of the First International Conference on Human Language Technology Research (HLT), San Diego, CA, 2001.
[27] E. Reiter, "NLG vs. templates," 1995 [Online]. Available: https://arxiv.org/abs/cmp- lg/9504013.
[28] X. Huang and A. Fiedler, "Proof verbalization as an application of NLG," Proceedings of the 15th International Joint Conference on Artificial Intelligence, San Francisco, CA, 1997, pp. 965-972.
[29] T. H. Wen, M. Gasic, N. Mrksic, P. H. Su, D. Vandyke, and S. Young, "Semantically conditioned LSTMbased natural language generation for spoken dialogue systems," Proceedings of the 2015 Conference on Empirical Methods in Natural Language Processing, Lisbon, Portugal, 2015, pp. 1711-1721.
[30] "A chatbot-based interactive question answering system," by S. Quarteroni and S. Manandhar, Proceedings of the 11th Workshop on the Semantics and Pragmatics of Dialogue, Trento, Italy, 2007, pp. 83-90.
[31] ALICE chatbot: trials and outputs," by B. A. Shawar and E. Atwell, Computación y Sistemas, vol. 19, no. 4, pp. 625-632, 2015.
[32] In Rajshahi, Bangladesh, during the 2015 International Conference on Computer and Information Engineering (ICCIE), M. S. Satu and M. H. Parvez reviewed integrated applications utilizing AIML-based chatbots, pp. 87-90.
[33] "Using dialogue corpora to train a chatbot," by B. A. Shawar and E. Atwell, Proceedings of the Corpus Linguistics Conference, pp. 681-690, Lancaster, UK, 2003.
[34] B. Setiaji and "Chatbot using a knowledge in database: human-to-machine conversation modeling," written by F. W. Wibowo, Proceedings of the 7th International Conference on Intelligent Systems, Modelling and Simulation (ISMS), Tokyo, Thailand, 2016, pp. 72–77.
[35] G. Antoniou and F. V. Harmelen, A Semantic Web Primer, 2nd ed. Cambridge, MA: MIT Press, 2008.
[36] K. O. Lundqvist, G. Pursey, and S. Williams, "Design and implementation of conversational agents for harvesting feedback in eLearning systems," in Scaling up Learning for Sustained Impact. Heidelberg, Germany: Springer, 2013, pp. 617-618.
[37] V. Devedzic, "Education and the Semantic Web." The International Journal of Artificial Intelligence in Education, volume 14, number 2, pages 165–191, 2004.
[38] A. Doan, J. Madhavan, P. Domingos, and "Learning to map between ontologies on the semantic web," Proceedings of the 11th International Conference on World Wide Web, Honolulu, HI, 2002, pp. 662-673, by A. Halevy.
[39] "Ontology learning for the semantic web," by A. Maedche and S. Staab, IEEE Intelligent Systems, vol. 16, no.2, pp. 72-79, 2001.
[40] T. Berners-Lee, J. Hendler, and O. Lassila, "The semantic web," Scientific American, vol. 284, no. 5, pp. 34-43, 2001.
[41] J. Han, J. Pei, and M. Kamber, Data Mining: Concepts and Techniques. San Francisco, CA: Morgan Kaufmann, 2011.
[42] B. Larsen and C. Aone, "Fast and effective text mining using linear-time document clustering," in Proceedings of the 5th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, San Diego, CA, 1999, pp. 16-22.
[43] M. W. Berry, Survey of Text Mining: Clustering, Classification, and Retrieval. New York, NY: Springer, 2004.
[44] A. H. Tan, "Text mining: the state of the art and the challenges," in Proceedings of the PAKDD 1999 Workshop on Knowledge Discovery from Advanced Databases, Beijing, China, 1999, pp. 65-70.
[45] J. I. Hong and J. A. Landay, "An infrastructure approach to context-aware computing," Human–Computer Interaction, vol. 16, no. 2-4, pp. 287-303, 2001.
[46] T. P. Moran and P. Dourish, "Introduction to this special issue on context-aware computing," Human–Computer Interaction, vol. 16, no. 2-4, pp. 87-95, 2001.
[47] P. Dourish, "Seeking a foundation for context-aware computing," Human–Computer Interaction, vol. 16, no. 2-4, pp. 229-241, 2001.
[48] J. I. Hong, "The context fabric: an infrastructure for context-aware computing," in Proceedings of CHI'02 Extended Abstracts on Human Factors in Computing Systems, Minneapolis, MN, 2002, pp. 554-555.
[49] N. A. Bradley and M. D. Dunlop, "Toward a multidisciplinary model of context to support context-aware computing," Human-Computer Interaction, vol. 20,
[50] "Artificial intelligence markup language: a brief tutorial," 2013 [Online], by M. D. G. B. Marietto, R. V. de Aguiar, G. D. O. Barbosa, W. T. Botelho, E. Pimentel, R. D. França, and V. L. da Silva. https://arxiv.org/abs/1307.3091 is accessible.
[51] B. A. Shawar and E. Atwell, "A comparison between Alice and Elizabeth chatbot systems," School of Computing, University of Leeds, UK, 2002.
[52] "Data mining curriculum a proposal (Version 1.0)," 2006 [Online], by S. Chakrabarti, M. Ester, U. Fayyad, J. Gehrke, J. Han, S. Morishita, G. Piatetsky-Shapiro, and W. Wang. https://kdd.org/exploration_files/CURMay06.pdf is accessible.
[53] "From Eliza to XiaoIce: challenges and opportunities with social chatbots," Frontiers of Information Technology & Electronic Engineering, vol. 19, no. 1, pp. 10-26, 2018, by H. Y. Shum, X. He, and D. Li.
[54] "Impact of agent's answers variability on its believability and human-likeness and consequent chatbot improvements," by M. Xuetao, F. Bouchet, and J. P. Sansonnet, in Proceedings of the 23rd Convention of the Society for the Study of Artificial Intelligence and Simulation of Behavior (AISB), Edinburgh, UK, 2009, pp. 31-36.
[55] J. Cahn, "CHATBOT: architecture, design, & development," Master of Science thesis, University of Pennsylvania, Philadelphia, PA, School of Engineering and Applied Science, 2017.
[56] "A survey of various chatbot implementation techniques," International Journal of Computer Engineering and Applications, vol. 11, issue no. 7, 2017, by A. Deshpande, A. Shahane, D. Gadre, M. Deshpande, and P. M. Joshi.

[57] Chatbot as personal assistant, International Journal of Applied Engineering Research, vol. 13, no. 20, pp. 14644-14649, 2018; G. Nair, S. Johnson, and V. Sathya.
[58] H. J. Won, “Introducing SK Telecom's rising star, Nugu,” 2018 [Online]. Available: http://www.koreaherald.com/view.php?ud=20180207000720.
[59] B. G. Kim, "KT's intelligent GiGa Genie assists and links users," 2017 [Online]. http://www.koreaherald.com/view.php?ud=20170927000730 is accessible.
[60] B. Jaekel, "Starbucks AI barista shifts mobile ordering and further reduces human interaction,"2017 [Online].The article https://www.retaildive.com/ex/mobilecommercedaily/starbucks-ai-barista-further-reduces-human-interaction-shifts-mobile-ordering is accessible



10.22214/IJRASET

45.98

IMPACT FACTOR: 7.129

IMPACT FACTOR: 7.429

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY