

The applications of chatbot

Zhuoyan Han*

Department of Computer Science and Technology Yanbian University Jilin China

* Corresponding Author Email: 2194021537@ybu.edu.cn

Abstract. A chatbot is a program that uses natural language to simulate a human conversation. and can receive questions from users to answer, as well as engage in casual conversation with users in a set format or help them complete a matter. It can free up personnel in an organization that is needed for reasonably stable, repetitive, and demanding tasks or procedures. Natural language processing (NLP), an essential aspect of artificial intelligence, forms the foundation of the system., and neural networks (NNs) that receive natural language and process responses. In recent years, chatbots have grown significantly with the rise of artificial intelligence, with achievements by major Internet companies, various universities, and research institutes. This review provides a detailed study of chatbots in five areas of intelligence in recent years, including education, intelligent question and answer, customer service, entertainment, and personal assistants. The goal is to summarize the cutting-edge and effective technologies in each area. In reviewing these papers, we pay closer attention to the technology in this paper's potential development possibilities and whether relevant experiments or detailed descriptions are done for the proposed future extensions, etc. While we discuss and study the current technologies, we also pay attention to the possibilities and trends in the development of new fields.

Keywords: chatbot; natural language processing; dialogue system; machine learning; artificial intelligence; deep learning.

1. Introduction

Chatbots played a crucial role in the development of natural language processing (NLP) in the 1960s before Turing made the Turing Conjecture more than a decade later. There were about three critical historical periods when chatbots developed from the 1960s to the end of the last century. To mimic psychologists in clinical therapy, Joseph Weizenbaum developed the chatbot ELIZA [1] at the Massachusetts Institute of Technology (MIT) in 1966. Even though ELIZA [1] was constructed with merely keyword matching and individual rules, it is noteworthy. A chatbot system called UC (UNIX Consultant) was developed by Robert Wilensky and other researchers at the University of California, Berkeley (UC Berkeley) [2] in the second period (1988). In addition to helping users learn how to use UNIX, UC offers support for other operating systems as well. This system was capable of analyzing the language of the user, determining the target of the user's operation, providing a plan to resolve the user's needs, determining the final conversation to be generated in English, and modeling the user based on his experience with the UNIX environment. As a result of the ELIZA chatbot, Dr. Richard S. Wallace created the ALICE system in the third period (1995), on which he based his work. Since 1998, ALICE has been open source, and currently, over 500 developers contribute code around the globe. ALICE is now widely used as a platform for developing virtual assistants for mobile devices due to AIML (Artificial Intelligence Markup Language). It is arguably the best-performing chatbot in its class, despite its use of heuristic template matching.

Instead of giving direct interaction with a live person who can communicate with individuals in the natural language sector, a chatbot is a software application was using to perform online chat conversations using text or text-to-speech. They also can be categorized into three types in general. Generation type, knowledge graph type, and retrieval type. The knowledge graph type chatbot is the most difficult to implement, but it has the most potential.

Chatbots can be classified into five different categories based on application scenarios: education, intelligent question answering, customer service, entertainment, and personal assistant. Chatbots that assist users in learning a specific language by creating an interactive language usage environment;

chatbots that guide users through learning and mastering a particular skill in-depth step by step; chatbots that assist users with certain experiences and understanding learning at a particular age, and so on. Learning and training goods with human and computer interaction, as well as children's intelligent toys, are instances of chatbot application scenarios. Chatbots are widely used in intelligent question-answering scenarios in market research, customer service, and some other scenarios where repetitive interactions commonly occur, or as a complement to the GUI purpose of providing users with an efficient framework that focuses or is even integrated seamlessly into hardware devices like smart speaker systems, home automation, and smart navigation, carrying the weight of human-computer interaction separately. In customer service scenarios, the primary purpose is to automatically respond to consumer issues associated with products, services, and business, to reduce enterprise customer service operation time and boost the experience for the user. Websites, mobile communication, and actual robots are commonly used to provide the service. Interacting with users on a limitless variety of topics (small talk) serves as friendship and relaxation in entertainment circumstances. Social media, children's friendship and amusement, and gaming coaching are among the application situations. They can give subject-specific services, also including assisting customers in asking about the weather and responding to inquiries about common knowledge of life, in addition to speaking with users on open topics. The major purpose of a personal assistant in a scenario is to assist consumers in managing their social calendars, shopping online, booking tickets, making hotel reservations, and so on. If you work in the finance industry, then the bot can help you with expense tracking, and if you work in the health industry, then the bot can help you with fitness tracking. In general, these types of scenarios are how bots handle the details of the user's life and become a great personal assistant to the customer.

2. Literature Review

In this section, chatbot papers from recent years are analyzed separately by the five categories in the introduction

2.1. Chatbots in education scenarios

Educational chatbots are chatbots that help users learn a certain kind of knowledge. It can be used to guide the user through a step-by-step process of learning and mastering the skill and can help the user with certain knowledge-assisted learning at a specific age. It can be used to lead and guide children and students in their development and professional skills.

A study by Kasthuri and Balaji [3] specified chatbots are one of the most convenient ways for students to learn, and they are also able to correct students' doubts at any time without human support. This study focused on a typical approach to designing chatbots for real MATLAB datasets so that Students can ask the chatbot questions in the form of text, which are then processed using Deep learning techniques and natural language processing. Finally, the chatbot can answer the student with accurate answers.

Collaboration is a factor that affects student learning, according to a study by A. J. Moraes Neto and M. A. Fernandes [4], and while learning management has been used to enable remote cooperation, describing and highlighting important aspects of learning process management cooperation to continuously engage learners remains a difficult problem. This research looked at how to employ academically effective dialogue structures to create and evaluate online collaborative learning, as well as how to encourage student conversation through the use of interventions.

Taking this concept further, A. Deveci Topal et al. [5] examined the impact of artificial intelligence-based chatbots on student achievement and perceptions of chatbots in a fifth-grade science lesson. The findings revealed that, while there were no differences in educational achievement between the control and treatment groups, the employment of the chatbot had a beneficial effect on the students in the experiment group's online learning experience.

On the other hand, a paper by F. Clarizia et. al. purposed to introduce a prototype for implementing chatbots in the education field. It was mostly about creating precise frameworks to control patterns of communication and provide pupils with the proper replies. So that the chatbot can use NLP techniques and the domain's ontology to recognize inquiries and deliver responses to students.

Chat programs, according to Heryandi [7], proposed that messages can be sent and received through an application programming interface (API). So that this API could be used to build chatbots that provide services to users through chats. The goal of this research was to create a chatbot using interactional technologies. The results demonstrated that the College may use this chatbot to provide students and parents with convenient and affordable access to academic records.

Individual education chatbots, according to Kowsher et al. [8,] will assist students to boost enthusiasm through self-study while reducing reliance on tutors and other technology. The goal of this research was to depict a human responding to user questions in Bengali in the quality education. It's a chatbot powered by AI, with a focus on Bengali natural language processing (BNLP) and machine learning algorithms. This research developed a closed field chatbot based on retrieval that will converse with people using pattern matching algorithms and learn through interactions to enhance its performance metrics. The results give a corpus of Bengali conversations that will aid in the development of a Bengali text processing research process.

The main premise identified by authors Hussain and Ginige [9] is that one of the most significant drawbacks of chatbots is the creation of a local base of knowledge. Conventional chatbot knowledge base systems are often created manually, which is a lengthy process that takes years to teach a chatbot a certain topic. This research focused on the Health Informatics Domain, which uses the wider public and diabetics to educate and control diabetes. VDMS - Virtual Diabetes Management System - is the name of this chatbot. The tool expands the knowledge base of a standard chatbot to a source of external knowledge, Wikipedia, from its local knowledge base. This study also adds an open-source AIML-based online chatbot for upgrading user-specific dialogues to the chatbot architecture to make talks with chatbots more relevant than earlier chat sessions.

2.2. Chatbots in Intelligent question answering scenarios

Intelligent question-answering that is astute Chatbots are commonly used in several different scenarios involving frequent and repeated chats, as well as a supplement to graphical user interfaces (GUI). It offers a quick and tailored experience to users. On the other hand, to enable human-computer connection, this chatbot can be connected and integrated into hardware digital assistants.

General question-answering chatbot systems require a local database, but a study by Abdul-Kader and Woods [10] proposed Creating a blank chatbot database and populating it with data from a website page or plain text corpus. Extracting data from a web page for this purpose necessitates a great deal of processing, as well as filtering and quantifying the plain text extracted, feature extraction, and rating classification. This research offered a new method for quantifying text responses from uninformed chatbots that uses numerous feature extraction approaches. To discover the best match to the query, multiple metrics are analyzed at the same time. By re-ranking, the scores of the retrieved features of the text reply, the closest matches with the top scores were found. The use of cosine similarity in word matching results in a significant boost in system performance. The query can be broken into more specialties in the future and utilized to enhance matching. To use a method to identify questions from responses, sentences retrieved from the plain text could be used to construct question-answer (Q/A) pairs. Chatbots can use the generated question/answer pairs as a knowledge base. This study, on the other hand, does not implement.

A study by Herbert and Kang [11] proposed known as Contextual MCRDR (C-MCRDR), context-based MCRDR is an extension of Multiple Classification Ripple Down Rules (MCRDR). to build a knowledge base of the real-time system. The RDR knowledge discovery technique makes it simple to maintain. This research also extended this approach to a teaching domain that generates offline course-related documents for evaluation purposes using a production database. This Chatbot system,

on the other hand, uses automatic speech recognition (ASR) to integrate audio chatbot interfaces, and the trial findings of a real-time, complete feedback scoring system reveal great user approval. The created system is expected to be easily used as a CA NLIDB utility in additional semantically richer fields, and it shows potential in single-domain and multi-domain situations.

To improve the efficiency of the algorithm, Sharma and Gupta [12] proposed to add deep learning methods to basic NLP algorithms to build models and implement various details and adjustments to produce better results. The study employed twenty tasks from Facebook's babI dataset. Most babI jobs can be solved with this model. Combining this network with the sophisticated Dynamic Memory Networks, (DMN+), introduced by Xiaong et al, can solve the problem of visual data.

A paper proposed by Kowsher et. al. [13] developed the Bangla Informative Question Answering System (BIQAS). Through Bengali Natural Language Processing (BNLP), it can assist users in tracking important information. This study analyzes various mathematical techniques for pre-processing data and establishing the association between user problems and questions containing information: the Naive Bayes algorithm, cosine similarity, and Jaccard similarity., and then calculates the accuracy of the answers by each of these three methods. but this paper does not introduce deep learning algorithms and apply them to a broader domain.

On the other hand, a study by Benjelloun Touimi et. al. [14] specified the current state of online educational platforms like Massive Online Open Courses (MOOC). Learners are unable to find useful information in a large amount of data and finding relevant information in forums is troublesome. Likewise, it is difficult for instructors to manage large numbers of learners. This study proposed the development of a Chabot who plays the role of assistant and mentor to learners and tutors. This study also proposed a new approach to answering learners' questions in a natural language chatbot in a relevant and immediate manner. The major method is that a model is built based on LDA Bayesian statistical methods, applied to threads posted in the forum, and classified to provide learners with rich semantic responses and enrich ChatBot's knowledge database. At the same time, we will map the extracted knowledge to ontologies to provide pedagogical resources for learners as learning support.

In recent years, due to the spread of COVID-19, Amer et. al. [15] proposed an intelligent chatbot that can respond to questions about the COVID-19 event. The main model is a Google BERT language model that has been pre-trained. This work introduced two architectural phases to the question-answering challenge based on BERT. To begin, the text classification algorithm is implemented using the BERT transformer., and then the BERT model is used to construct the queried domain of the answers. The dataset used is Stanford's SQuAD V2.0 for testing. However, this paper does not introduce more data sets to enrich the accuracy and robustness of the model.

2.3. Chatbots in customer service scenarios

Customer service chatbots are mainly used to automatically respond to questions from users related to products, services, and businesses. It can solve users' problems promptly and reduce the stress of customer service for enterprises.

A study by Xu et. al. [16] specified that customers frequently utilize social media to ask for or receive service. However, the majority of requirements are either not handled or are not handled at all. This research developed a new dialogue Chatbot system that responds to customer requests on social media automatically. The major approach is a deep learning technique that uses Twitter conversations of users and agents as a dataset for training modeling. The major approach is a deep learning technique that uses Twitter conversations of users and agents as a dataset for training modeling. More than 40% of the requests were derived to be emotional, and in terms of exhibiting empathy and assisting users in coping with high-stress situations, this system was comparable to or better than information retrieval methods developed on automatic evaluation criteria and human judgment.

On the other hand, another study by Ngai et. al. [17] proposed a conversational agent Chatbot built on knowledge of marketing and e-commerce sales. This paper tested a customer service chatbot against a company through web crawlers, natural language processing, and other techniques. The

study also discussed in detail the challenges of system implementation and lessons learned that would guide the future development of this system.

Behera et. al. [18] proposed personalized contextual customer service using cognitive chatbots. This study collects data from 300 respondents from business-to-business (B2B) companies. Improved customer service, especially the capacity to examine genuine product and service information while automatically answering repetitious questions based on available data. The cognitive chatbots described in this paper are effective tools for assisting customers with a wide range of wishes and needs. Although their capabilities and benefits, intelligent chatbots cannot yet ensure excellent customer service for B2B use scenarios, nor can they replace human interaction.

The main problem identified by authors Zhu et. al. [19] is the unsatisfactory results of traditional chatbots for handling multiple rounds of questions. This paper proposed an information retrieval-enhanced chatbot called Lingke, which can answer questions and handle multiple rounds of questions based on the given product introduction document. This paper also proposes a refined pipeline processing system for refining unstructured document-based responses and providing suitable and continuous context-response matching for multi-round conversations. This paper takes e-commerce product introductions as an example, and can be extended to other domains and add an intent monitoring mechanism to try to find solutions for how to handle introductory documents containing multiple objects, but is not implemented in the paper.

Cui et. al. [20] proposed a customer support chatbot that makes use of currently accessible e-commerce data on a massive scale, called SuperAgent. To make it more feasible and cost-effective to react to repeated questions, it used information from in-page product details and consumer content from e-commerce websites. This paper tested SuperAgent as a browser extension and shows users how useful it is for online shopping. However, this paper does not explore in depth the multi-round query.

Authors Flstad et al. [21] recognized the key concept as elements affecting users' confidence in chatbots and conducted an individual interview. The quality of the interpretation of asks and suggestions, likeness to humans, branding, security, and privacy were all found to influence consumer trust in chatbots employed for customer support in this study. Users must trust chatbots in order for them to reach their full potential in customer support, according to this report.

2.4. Chatbots in entertainment scenarios

Entertainment chatbots mainly chat with users, thus playing the role of companionship, comfort, and so on. It is used in scenarios such as child and elderly companionship, artificial voice assistant, mental state detection, and psychological counseling. It could provide services on specific themes in addition to speaking with users on open topics.

Taking this idea forward de Arriba-Pérez et. al. [22] proposed most of the previous therapeutic testing systems for cognitive impairment were based on manual testing, which led to excessive caregiving and white-coat effects. To address these issues, this research presents a chatbot system that both entertains and transparently monitors cognitive decline in elderly persons. During the conversation phase, this automated chatbot assesses cognitive abilities by using a machine-required algorithm to detect cognitive impairments, creating a conversation stream from the latest information using natural language generation methods, and comparing the similarity metrics of these answers to the user's reactions. The findings of this study show that this chatbot has a lot of potential for long-term, user-friendly therapy monitoring for older persons.

A study by Sharma et. al. [23] also proposed a cognitive-behavioral treatment system or a therapy chatbot that caters to the user's health and information demands. This chatbot system focused on detecting individual depression levels and detecting individual-specific remedies for depression levels, thus helping people fight depression. The main design approach of this thesis is a chatbot that can mimic a psychotherapist.

The main problem identified by García-Méndez et. al. [24] is that Many mass-market sectors have yet to be applied to older individuals, making them particularly susceptible to the digital gap. This

study suggested EBER, a chatbot that tries to bridge the digital divide for elders. In addition, this research introduced the novel notion of "intelligent radio," which would deliver background news through voice dialogues to improve interaction with seniors. By integrating words taken from users' answers to chatbot inquiries with keywords generated from news events, this chatbot's system may access digital content of interest. Based on the representation of the word space, this technique permitted the development of a metric of the user's abstraction capabilities. However, personalization elements to guide the dialogue have yet to be incorporated in this article.

Patel et. al. [25] proposed a chatbot that developed significant emotional bonds with its users. It used the user's chat data to assign text to sentiment tags and to determine the user's psychological condition. Three deep learning classifiers were used in this study: a convolutional neural network (CNN), a hierarchical attention network (HAN), and a recurrent neural network (RNN). In addition, this chatbot approach was domain-specific. Communicating with the user and thus preventing pessimistic behaviors, had some ideological implications for relieving emotional stress and stopping pessimistic behaviors.

To construct such a chatbot for college students' mental relaxation, Bopage and Weerakoon [26] proposed using NLP techniques and dense neural networks. The most important element is to recognize and respond to pupils' intentions. Text is used for both input and output. The main problem with this system is the collection of data for the main database because the consultant's conversations are confidential. The biggest limitation is the inability to think with intelligence and compassion like a real human being. In addition, it is difficult to handle hyper-phrases, synonyms, and hyper-phrases since the chatbot only knows specific terms. In the face of these problems, this article suggests some improvements that can be made to expand the range of capabilities of chatbots. By integrating voice message input, multilingual support, and creating different dynamic versions of chatbots, but not yet implemented.

2.5. Chatbots in personal assistant scenarios

Personal assistant chatbots are helping customers manage their social schedules, book flights, and hotels, and do other personal business. A bot in this type of scenario is a personal assistant that handles the details of the user's life.

A study by Mashud and Wisda [27] proposed a web-based personal assistant chatbot that assists clients by swiftly answering their inquiries and providing them with the information they require without the work and exertion of staff. This study employed surveys and interviews to collect primary and secondary data from company papers, as well as various forms of Unified Modeling Language (UML) diagrams to configure black-box testing methodologies. This chatbot can create a chatbot program that can rapidly and accurately answer questions entered by customers after conducting research from websites.

Another study by Nair et. al. [28] proposed an artificially intelligent personal assistant chatbot as a resume. This chatbot form of resume work can be used as a new generation product in the field of application. The chatbot will help the recruiter to understand your personality as well as your details. This system will communicate with the user. Natural language processing is used to help with this and AIML files. In addition, this chatbot can be used to improve the lives of ordinary people, as a personal life assistant.

Pham et. al. [29] proposed a personal assistant chatbot for English learning called English Practice that is installed on mobile devices and interacts with users through windowed chats. In addition, it can automatically remind learners of their studies and helps them learn vocabulary and new lessons. The study's findings reveal that most of the system's core functionalities are employed by users with good outcomes, however this report does not go into detail about other uses.

On the other hand, Dibitonto et. al. [30] proposed a personal assistant Chatbot called Link Student Assistant (LISA). This system is designed to help students with information and services through chatbots for campus life. This study focused on understanding which information and services can be better accessed, which components of intellectual ability should be exploited, and how the qualities

of chatbots affect the experience for users. The findings suggest that it is necessary to introduce some characteristics such as empathy and sensitivity to design the LISA personality, which will better help students.

A study by Spournias et. al. [31] proposed a personal assistant Chatbot, a human-machine dialogue, and provides human-machine interface (HMI) functionality. The primary premise of this system is to recognize the context and phrases in the user's inquiry, respond correctly to the question, and then deliver an answer based on an analysis of the words in the question and the terms in its database. In this paper, the chatbot system is used in smart homes and assisted living environments so that the home robot can be controlled by the human voice in Greek. In addition, this personal assistant chatbot can be used in other areas of user assistance, but no experiments were conducted in this paper.

3. Conclusion

The review of the literature above shows that chatbots have been experimented with in all major fields. Chatbot systems have also been integrated into people's lives in a very convenient way. Moreover, by studying many papers, it is clear from only that although chatbots have been tried to be used in many fields, most of the papers do not have a very complete mention of their technology and their degree of reproduction is difficult. Among the techniques include specific language processing techniques, specific operations of machine learning or deep learning algorithms, detailed processing of datasets and whether they are adapted for unstructured data, etc. Most of the paper studies aim to explore possible types of applications related to this area of chatbots, but many technical difficulties are still difficult to overcome. Some of the papers use deep learning approaches that perform better compared to machine learning, but the depth of exploration is still shallow. For exploring technologies in the field of chatbots, there is still a lot of room for natural language processing, a basic step that can lead to more accurate data. Improvements in the processing of unstructured conversational data also have broad implications and require further and deeper research. Therefore, today's research on chatbots should not be limited to the study of their application to a specific domain and their specific implementation, but should also focus on the basic data, i.e., natural language processing, to bring better results.

References

- [1] J. Weizenbaum, "ELIZA—a computer program for the study of natural language communication between man and machine," *Commun. ACM*, vol. 9, no. 1, pp. 36–45, Jan. 1966, doi: 10.1145/365153.365168.
- [2] R. Wilensky, "The Berkeley UNIX Consultant Project," in *Wissensbasierte Systeme*, Berlin, Heidelberg, 1987, pp. 286–296. doi: 10.1007/978-3-642-88719-2_25.
- [3] E. Kasthuri and S. Balaji, "A Chatbot for Changing Lifestyle in Education," in 2021 Third International Conference on Intelligent Communication Technologies and Virtual Mobile Networks (ICICV), 2021, pp. 1317–1322. doi: 10.1109/ICICV50876.2021.9388633.
- [4] A. J. Moraes Neto and M. A. Fernandes, "Chatbot and Conversational Analysis to Promote Collaborative Learning in Distance Education," in 2019 IEEE 19th International Conference on Advanced Learning Technologies (ICALT), Jul. 2019, vol. 2161–377X, pp. 324–326. doi: 10.1109/ICALT.2019.00102.
- [5] A. Deveci Topal, C. Dilek Eren, and A. Kolburan Geçer, "Chatbot application in a 5th grade science course," *Educ Inf Technol*, vol. 26, no. 5, pp. 6241–6265, Sep. 2021, doi: 10.1007/s10639-021-10627-8.
- [6] F. Clarizia, F. Colace, M. Lombardi, F. Pascale, and D. Santaniello, "Chatbot: An Education Support System for Student," in *Cyberspace Safety and Security*, Cham, 2018, pp. 291–302. doi: 10.1007/978-3-030-01689-0_23.
- [7] A. Heryandi, "Developing Chatbot For Academic Record Monitoring in Higher Education Institution," *IOP Conf. Ser.: Mater. Sci. Eng.*, vol. 879, no. 1, p. 012049, 2020, doi: 10.1088/1757-899X/879/1/012049.
- [8] Md. Kowsher, F. S. Tithi, M. Ashraful Alam, M. N. Huda, M. Md Moheuddin, and Md. G. Rosul, "Doly: Bengali Chatbot for Bengali Education," in 2019 1st International Conference on Advances in Science,

- Engineering and Robotics Technology (ICASERT), 2019, pp. 1–6. doi: 10.1109/ICASERT.2019.8934592.
- [9] S. Hussain and A. Ginige, “Extending a conventional chatbot knowledge base to external knowledge source and introducing user based sessions for diabetes education,” in 2018 32nd International Conference on Advanced Information Networking and Applications Workshops (waina), Los Alamitos, 2018, pp. 698–703. doi: 10.1109/WAINA.2018.00170.
- [10] S. A. Abdul-Kader and J. Woods, “Question answer system for online feedable new born Chatbot,” in 2017 Intelligent Systems Conference (IntelliSys), Sep. 2017, pp. 863–869. doi: 10.1109/IntelliSys.2017.8324231.
- [11] D. Herbert and B. H. Kang, “Intelligent conversation system using multiple classification ripple down rules and conversational context,” *Expert Syst. Appl.*, vol. 112, pp. 342–352, Dec. 2018, doi: 10.1016/j.eswa.2018.06.049.
- [12] Y. Sharma and S. Gupta, “Deep Learning Approaches for Question Answering System,” *Procedia Computer Science*, vol. 132, pp. 785–794, Jan. 2018, doi: 10.1016/j.procs.2018.05.090.
- [13] Md. Kowsher, M. M. M. Rahman, S. S. Ahmed, and N. J. Prottasha, “Bangla Intelligence Question Answering System Based on Mathematics and Statistics,” in 2019 22nd International Conference on Computer and Information Technology (ICCIT), 2019, pp. 1–6. doi: 10.1109/ICCIT48885.2019.9038332.
- [14] Y. Benjelloun Touimi, A. Hadioui, N. El Faddouli, and S. Bennani, “Intelligent Chatbot-LDA Recommender System,” *Int. J. Emerg. Technol. Learn.*, vol. 15, no. 20, pp. 4–20, 2020, doi: 10.3991/ijet.v15i20.15657.
- [15] E. Amer, A. Hazem, O. Farouk, A. Louca, Y. Mohamed, and M. Ashraf, “A Proposed Chatbot Framework for COVID-19,” in 2021 International Mobile, Intelligent, and Ubiquitous Computing Conference (MIUCC), 2021, pp. 263–268. doi: 10.1109/MIUCC52538.2021.9447652.
- [16] A. Xu, Z. Liu, Y. Guo, V. Sinha, and R. Akkiraju, “A New Chatbot for Customer Service on Social Media,” in *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems*, New York, NY, USA, 2017, pp. 3506–3510. doi: 10.1145/3025453.3025496.
- [17] E. W. T. Ngai, M. C. M. Lee, M. Luo, P. S. L. Chan, and T. Liang, “An intelligent knowledge-based chatbot for customer service,” *Electronic Commerce Research and Applications*, vol. 50, p. 101098, Nov. 2021, doi: 10.1016/j.elerap.2021.101098.
- [18] R. K. Behera, P. K. Bala, and A. Ray, “Cognitive Chatbot for Personalised Contextual Customer Service: Behind the Scene and beyond the Hype,” *Inf Syst Front*, Jul. 2021, doi: 10.1007/s10796-021-10168-y.
- [19] P. Zhu, Z. Zhang, J. Li, Y. Huang, and H. Zhao, “Lingke: A Fine-grained Multi-turn Chatbot for Customer Service,” *arXiv*, arXiv:1808.03430, Aug. 2018. doi: 10.48550/arXiv.1808.03430.
- [20] L. Cui, S. Huang, F. Wei, C. Tan, C. Duan, and M. Zhou, “SuperAgent: A Customer Service Chatbot for E-commerce Websites,” in *Proceedings of ACL 2017, System Demonstrations*, Vancouver, Canada, 2017, pp. 97–102. doi: 10.18653/v1/P17-4017.
- [21] A. Følstad, C. B. Nordheim, and C. A. Bjørkli, “What Makes Users Trust a Chatbot for Customer Service? An Exploratory Interview Study,” in *Internet Science*, Cham, 2018, pp. 194–208. doi: 10.1007/978-3-030-01437-7_16.
- [22] F. de Arriba-Pérez, S. García-Méndez, F. J. González-Castaño, and E. Costa-Montenegro, “Automatic detection of cognitive impairment in elderly people using an entertainment chatbot with Natural Language Processing capabilities,” *J Ambient Intell Human Comput*, Apr. 2022, doi: 10.1007/s12652-022-03849-2.
- [23] B. Sharma, H. Puri, and D. Rawat, “Digital Psychiatry - Curbing Depression using Therapy Chatbot and Depression Analysis,” in 2018 Second International Conference on Inventive Communication and Computational Technologies (ICICCT), Apr. 2018, pp. 627–631. doi: 10.1109/ICICCT.2018.8472986.
- [24] S. García-Méndez, F. De Arriba-Pérez, F. J. González-Castaño, Jos. A. Regueiro-Janeiro, and F. Gil-Castiñeira, “Entertainment Chatbot for the Digital Inclusion of Elderly People Without Abstraction Capabilities,” *IEEE Access*, vol. 9, pp. 75878–75891, 2021, doi: 10.1109/ACCESS.2021.3080837.
- [25] F. Patel, R. Thakore, I. Nandwani, and S. K. Bharti, “Combating Depression in Students using an Intelligent ChatBot: A Cognitive Behavioral Therapy,” in 2019 IEEE 16th India Council International Conference (INDICON), 2019, pp. 1–4. doi: 10.1109/INDICON47234.2019.9030346.

- [26] H. Bopage and C. Weerakoon, “Mind Relaxation Chatbot for University Students by Using Dense Neural Network,” in 2021 5th SLAAI International Conference on Artificial Intelligence (SLAAI-ICAI), 2021, pp. 1–6. doi: 10.1109/SLAAI-ICAI54477.2021.9664678.
- [27] M. Mashud and W. Wisda, “Aplikasi Chatbot Berbasis Website sebagai Virtual Personal Assistant dalam Pemasaran Properti,” *Inspiration: Jurnal Teknologi Informasi Dan Komunikasi*, vol. 9, no. 2, pp. 99–107, 2019, doi: 10.35585/inspir.v9i2.2497.
- [28] G. Nair, S. Johnson, and V. Sathya, “Chatbot as a personal assistant,” *International Journal of Applied Engineering Research*, vol. 13, no. 20, pp. 14644–14649, 2018.
- [29] X. L. Pham, T. Pham, Q. M. Nguyen, T. H. Nguyen, and T. T. H. Cao, “Chatbot as an Intelligent Personal Assistant for Mobile Language Learning,” in *Proceedings of the 2018 2nd International Conference on Education and E-Learning*, New York, NY, USA, 2018, pp. 16–21. doi: 10.1145/3291078.3291115.
- [30] M. Dibitonto, K. Leszczynska, F. Tazzi, and C. M. Medaglia, “Chatbot in a Campus Environment: Design of LiSA, a Virtual Assistant to Help Students in Their University Life,” in *Human-Computer Interaction. Interaction Technologies*, Cham, 2018, pp. 103–116. doi: 10.1007/978-3-319-91250-9_9.
- [31] A. Spournias et al., “Experimental Evaluation of a Novel Personal Assistant in Greek Language for Ambient Assisted Living Environments employing home robots,” in *2018 South-Eastern European Design Automation, Computer Engineering, Computer Networks and Society Media Conference (SEEDA_CECNSM)*, Sep. 2018, pp. 1–9. doi: 10.23919/SEEDA-CECNSM.2018.8544920.