



A SURVEY ON VARIOUS CHATBOTS

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Abstract : In the modern world, people are always on the lookout for new information and ways to learn. However, it can be time-consuming and difficult to find the information we need through traditional methods, such as books, search engines, and online Encyclopedias. Chatbots can provide instant information to the queries in a various of sectors, which includes banking, retail, travel, healthcare, and education. Chatbots are computer applications which are created to imitate real-world user chats. They are powered by artificial intelligence (AI) and natural language processing (NLP) technologies, which enables them to understand human language and respond to it. Chatbots can be employed to carry out activities, offer information, and respond to queries. In this Paper we surveyed various methodologies of chatbot implementation, which includes Long Short-Term Memory (LSTM), Natural Language Generation (NLG), Supervised Machine Learning (SVM), Model Driven Engineering (MDE), Dialogue Management, Human-in-the-Loop (HITL), Audio-Frame Mean Expression (AFME), Random Forest, Support Vector Machine (SVM), Recurrent Neural Network (RNN), and Convolutional Neural Network etc. the cutting-edge methodologies. These techniques are used to create chatbots with more complex natural language comprehension and response capabilities. This paper's objective is to review and contrast several chatbot development approaches in order to determine which is optimal for certain applications. Finally this paper concluded that there are various methodologies and algorithms to implement a chatbot but every method has its own priority based on the specific task requirement, however methodologies evaluation accuracies and suggestion were presented in this survey paper.

IndexTerms - Chatbot, Artificial Intelligence, Natural Language Processing.

I. INTRODUCTION

Computer programs known as chatbots replicate conversations with human users by utilizing conversational AI technologies. They frequently work in customer service and healthcare settings where they may respond to inquiries, offer assistance, and find solutions to problems. Additional uses for chatbots include marketing, sales, and education. Chatbots can make our lives easier, more convenient, and more enjoyable in a number of ways. They can answer our questions 24/7, provide personalized recommendations and suggestions, automate many customer service task, to reach customers on a variety of channels, and personalize the customer experience by learning about each customer's preferences. Chatbots are still under development, but they having the ability to drastically alter how we communicate with machines. They are a powerful tool that can be used to improve customer service, reduce costs, and increase efficiency. Students who are struggling with a particular concept or who need more individualized attention can benefit from chatbots in education. Chatbots can make learning more engaging and participatory, which can improve students' learning experiences and increase their interest in the material.

This paper discusses the key technologies that are available for building chatbot for education purpose. In this paper, The vanishing gradient problem is addressed by storing long-term information in a memory cell. Natural Language Generation (NLG), which produces natural language text by using structured data as input. From labeled data, Supervised Machine Learning (SVM) learns that each data point has a known result or label Model. Driven Engineering (MDE), a potent chatbot development platform, may assist businesses in creating high-quality chatbots more quickly and effectively. Dialogue management, which uses both a statistical model and a rule-based system, is in charge of making sure that the discussion goes smoothly and that the user's intent can be recognized by the system and responded to. HITL tasks include fraud detection, object detection, picture classification, and medical diagnosis. AFME (Audio-Frame Mean Expression), a feature extraction approach used in speech processing and music information retrieval, is generated by averaging the values of all samples in an audio frame. A large number of decision trees are built by Random Forest, which then bases forecasts on the trees' consensus votes. Support Vector Machine (SVM) divides the data points into their corresponding classes by locating a hyperplane. And Convolutional Neural Network, both of which have the ability to learn spatial hierarchies in data, is particularly well suited for tasks like picture classification, object detection, and semantic segmentation. A universal solution does not exist to this problem, and the best strategy will be based on the unique circumstances.

There are many methodologies available in front of the developer as said earlier, the main hurdle is that, which methodology have to be chosen for their application is the big challenge. The objective of this survey paper is to facilitate researcher to choose appropriate methodology for their application. The survey paper analyse various methodologies of chatbot and evaluation results presented in the comparison table.

II. RELATED WORK

S. Venus Jin & Seounmi Youn . (2022). Examine the factors that influence consumers' intention to continue utilizing chatbots with AI. Social presence, imagery processing, and psychological ownership are all positively correlated with chatbot continuance intention. They used a combination of methods and technologies to collect and analyze data. The authors conducted a survey of 372 participants who had interacted with a chatbot in the past six months and used statistical analysis software to analyze the survey data, the correlations between social presence, imagery processing, and chatbot continuance intention using Pearson's correlation coefficient. Using multiple regression analysis, they were able to identify the significant chatbot continuation intention predictors. The links between social presence, imagery processing, psychological ownership, and chatbot continuing intention were investigated using route analysis in the study. The study provides useful information about the elements that affect users' intentions to keep using chatbots powered by AI. The results of this study can be used to create chatbots by programmers and designers that are more engaging and effective.[4]

Sanjay Chakraborty, Hrithik Paul et al.(2022). have developed a chatbot named Kiwi that can be used to promote infectious disease prevention and cure. The chatbot uses a variety of technologies and methods, including Recurrent Neural Networks (RNNs), decision trees, machine learning (ML), Python and a deep feedforward multilayer perceptron (MLP) model for infectious disease prediction which is trained on a dataset of infectious disease cases and learns to identify patterns in the data that are associated with different infectious diseases. It can provide doctor contact details, hospital addresses, oxygen cylinder contact details, disease symptoms, prevalence, diagnosis, and treatment procedures and concluded that It uses TensorFlow to build an NLP model that can make accurate predictions for user queries even when they are not contained in the training dataset. [5]

Vorada Sotiyanurak, Nittayapa Klangpornkun et al.(2021).describe the development and evaluation of a chatbot that counsels people who have experienced sexual assault on legal matters. The chatbot, called LAW-U, was developed using a combination of NLP, ML, and text summarization to train LAW-U. They first used NLP to extract the keywords from the Supreme Court cases. Then, they used ML to train the chatbot to identify the most relevant Supreme Court cases for each user's input, and also uses NLU to understand the user's query and identify the relevant legal issues, Information retrieval (IR) to retrieve the Supreme Court rulings that are most relevant to the user's query. Finally, they used text summarization to provide the user with a summary of Supreme Court cases. The chatbot can answer questions about a variety of legal topics related to sexual violence, such as the rights of victims, the available legal remedies, and the process of filing a lawsuit. The authors concluded that LAW-U has the potential to be a valuable resource for sexual violence victims.[6]

Silvia García-Méndez et al.(2021).describes the development and evaluation of an entertainment chatbot for elderly people with limited abstraction capabilities. The chatbot, called EBER, was developed using a combination of artificial intelligence techniques, including NLG, combination of NLG, sentiment analysis, and a word space represented spatially to provide users with a personalized and engaging experience. EBER is designed to provide entertainment to elderly people. It can read news, tell jokes, and play games. EBER can also adapt its reactions to a user's emotional state. The authors evaluated EBER with a sample of senior citizens with inadequate abstract thinking skills. The results showed that EBER was able to provide entertainment and companionship to the participants. The authors concluded that EBER has the potential to be a valuable tool for the digital inclusion of elderly people.[7]

Antonello Meloni, Simone Angioni et al.(2023). proposed AIDA-Bot which is a conversational agent that can interact with SKGs. It is based on parsing, query building, and answer generation. AIDA-Bot has been implemented in four different ways: as an Alexa skill, a web application, a Telegram bot, and an NAO humanoid robot. The algorithm proposed in the paper is called the Natural Language Query Processing (NLQP) algorithm. This is a novel approach to interacting with knowledge graphs, as it allows users to communicate with it using natural language way. This gives output by using user entities like telegram, browser etc.. There is need to develop more advanced techniques to enable chatbots to react to more sophisticated queries. [8]

Lenin Medeiros and Tibor Bosse et al.(2022). proposed a chatbot to reduce stress levels by mapping stress features and providing strategies to provide emotional support to the user input. Here, text mining and NLP are used to combine the stress features with the strategies. The experiment is conducted in three groups which the support is given by the chatbot or human is nothing. Interacting with chatbot can decrease stress levels and the chatbot gives equal support to human interaction.[9]

The authors of the paper Silvia T. Acuna and Oscar Dieste,(2022). have proposed chatbots which are being used in education. The paper presents a thorough mapping investigation on chatbot usability evaluation. It analyzes over 700 sources and identifies 28 primary studies. Statistical tests such as ANOVA, MANOVA, t-tests, Wilcoxon tests, and Mann-Whitney tests for data analysis. By using these tests, we can enhance the user experience with the chatbot. The paper provides insights into the benefits of conducting experiments to evaluate chatbot usability and suggests future directions for study in this discipline. Based on the findings, the paper outlines future research directions in chatbot usability evaluation guiding researchers towards areas that require further investigation.[10]

Addi Ait-Mlouk and Lili Jiang,(2020). proposes a knowledge graph-based chatbot that can generate SPARQL queries to obtain information from knowledge bases. The KBot architecture consists of three main components: a user interface, a natural language understanding (NLU) module, and a knowledge base access module. The paper also describes the implementation of KBot which was implemented using Jena and evaluated on a dataset of natural language queries. It was able to understand and answer the majority of the queries correctly. The paper concludes by discussing the limitations of KBot and the future work that could be done to improve it.[11]

Daniel Carlander-Reuterfelt et al.(2020). proposes a chatbot that can answer questions about data science and machine learning. The chatbot is called JAICOB. The paper begins by discussing the challenges of building a chatbot for data science then propose an architecture in support of JAICOB that solves these issues. JAICOB uses dialogue management, code generation, and natural

language understanding (NLU) to understand natural language queries, generate code, and maintain conversations with users. The paper concludes by Despite these challenges, the use of cognitive assistants in education has the ability to transform how we teach and learn.[12]

In this paper, Liang Zhang, Yan Yang, Jie Zhou, Chengcai Chen and Liang He .(2020). propose a retrieval-polished response generation method for chatbots which is a two step process. The method first retrieves a set of candidate responses from a large dataset of text and code. The candidate responses are then polished by a language model to improve their fluency and informativeness by using Keyword Matching, Natural Language Processing (NLP) techniques .The authors evaluated the proposed method on a variety of tasks and showed that it can generate more fluent and informative responses than traditional chatbots. The conclusion of the paper is that the proposed method is a promising approach for generating fluent and informative responses for chatbots.[13]

Gwendal Daniel, Jordi Cabot, Laurent Deruelle and Mustapha Derras.(2020). introduce Xatkit, a low-code chatbot development framework that supports multimodal interaction. Xatkit is designed to make it easy to develop chatbots without requiring a lot of code or knowledge of natural language processing. Xatkit is a modular, low-code, multimodal chatbot development framework which uses Natural Language Processing (NLP) approaches are used to determine the user's purpose and create responses that are relevant and coherent, Deep Learning (DL) algorithms are used to train language models that can interpret and generate human language more accurately, while Machine Learning (ML) techniques are used to learn from user interactions and enhance the chatbot's performance over time. This means that it is made up of smaller, independent components that are easy to customize and extend. They concluded that Xatkit is a powerful and easy-to-use chatbot development framework. The authors suggest that future work on Xatkit could focus on improving its natural language processing capabilities, user interface, and integration with other systems.[14]

Paula Maddigan And Teo Susnjak.(2023). focuses on using Large Language Models (LLMs) to convert natural language queries into data visualizations (NL2VIS). It confirms that LLMs are effective in this NL2VIS task when backed by well-engineered prompts. It provides an overview of the paper's structure and organization. These LLMs are pre-trained deep-learning models based on transformer architectures. Future research could focus on conducting user studies and obtaining feedback from end-users to evaluate the real-world usability and user-friendliness of NL2VIS systems like Chat2VIS.[15]

Yang Ye, Hengxu You and Jing Du.(2023). proposed "Improved Trust in Human-Robot Collaboration With ChatGPT". The study explores the use of ChatGPT, an AI language model, in human-robot collaboration (HRC) to enhance trust and performance. A 15-participant human-subject experiment was conducted, comparing fixed verbal commands and ChatGPT-controlled robot assistance in an assembly task. It uses a "dual-stage impedance control" algorithm for understanding the robot arm's movement. Future research should explore effective HRC workflows, enhanced AI model training could address issues related to miscommunication and inaccurate decisions. The Reduced cognitive load was observed when working with ChatGPT. Finally, The research indicates ChatGPT's potential for enhancing trust and performance in HRC. [16]

Angelo Salatino and Francesco Osborn.(2023) proposed the response given by the chatbot by integrating knowledge graphs and Conversational Agents. Here, the Conversation Agent is a computer program that understands natural language and gives responses. Knowledge graphs are the databases that store the graphs related to text, images, and videos. The authors developed a chatbot named AIDA -Bot to give responses. They used methods for processing natural language include entity recognition, entity linking, and semantic parsing are examples of approaches, to retrieve relevant information from the user's queries and map them to the knowledge graph. The result of the project is to answer the queries related to scientific articles, researchers, and institutions.[17]

In this paper, the authors, Tzu-Yu et al.(2023) propose a multimodal chatbot for intelligent manufacturing. The chatbot is designed to help workers with tasks such as assembly, maintenance, and troubleshooting. It can understand natural language queries and provide answers or instructions in a variety of ways, including text, speech, and images. The YMC model is a basic yet effective method for capturing video information for the purpose of user intent categorization. The results of the studies revealed that the YMC model functions somewhat superior to the YOLOv3 model. This is because YOLOv4 is a more accurate object detection model. They believe that the chatbot has the ability to increase efficiency and productivity of manufacturing operations.[18]

Giovanni Almeida et al.(2023).proposes a Computational Meaning Processing(CMP) methodology for managing and evolving the content of chatbot systems. Which is separated into three sections according to the experiences gained during development Evatalk, the chatbot for the Brazilian Virtual School of Government. The paper evaluated the proposed methodology by applying it to the development of the Evatalk chatbot. The results revealed that the methodology was successful in improving the chatbot's performance, reducing its human hands-off rate, increasing its knowledge base, and keeping the user satisfaction stable.[19]

Shahid, M. A. Hossain, S. S. I. Ahad, M. B. M. Al-Mamun, and N. K. Alam. (2022) proposed Survey on Detecting Fake News Spreaders". In the digital age, online social networks (OSNs) like Facebook and Twitter are central to modern life, serving as platforms for communication, self-expression, and news consumption. It emphasizes the significance of detecting and categorizing fake news spreaders on social media platforms. This outlines the primary categories used to classify spreaders based on source, propagation, and target features. Researchers may use machine learning algorithms like Random Forest, Support Vector Machine (SVM), or deep learning models such as RGA, based on the requirements of their experiments and the type of features they are analyzing. Future work should focus on developing platform-independent classifiers for detecting fake news spreaders across various social media platforms.[20]

Kulothunkan Palasundram ,et al.(2023) proposed "Enhancements to the Sequence-to-Sequence-Based Natural Answer Generation Models". The NLP algorithm for answer generation uses the Seq2Seq Model with Attention Mechanism, and Seq2Seq Model Prediction (Beam Search) used for this paper. The future work includes enhancement of data and use of advanced algorithms,

Fine-tune model parameters to maximize performance Conducting real-world testing, and considering scalability for practical deployment. Finally, Artificial intelligence (AI) has made significant strides, enabling machines to perform tasks once exclusive to human intelligence.[21]

Martha T. Teye 1, et al. (2022) proposed Understanding Culture, Context and Environment in Emotion Detection. Emotions are essential in human social life, and their detection is crucial in human-AI interactions. They introduce the concept of the AFME algorithm for emotional validation and outline the data preprocessing steps. The paper explores using Convolutional Neural Networks (CNN) for emotion recognition in both speech and facial expression data. Emphasizing the significance of both speech (audio) and image frames associated with speech, the paper highlights the role of context, rate of speech, and non-verbal communication cues. Future research should focus on differentiating features in emotion recognition among diverse demographic groups.[22]

Soufia Kausar, Bilal Tahir, And Muhammad Amir Mehmood (2022) introduce the Push-To-Trend framework for identifying trend promoters in Twitter hashtags. And highlights the language-independent nature of the framework, making it applicable to various languages. It discusses the framework's potential for demographics and sentiment analysis. It makes use of classifiers like Logistic Regression (LR), Decision Tree (DT), and Random Forest (RF) for performance evaluation. It needs to extend the framework to analyze trends and trend promoters across multiple social media platforms, such as Facebook, Instagram, or YouTube. This expansion would provide a more comprehensive view of online trend dynamics.[23]

Chen Li 1,(Member, Ieee), et al. (2022) proposed "ToD4IR: A Humanised Task-Oriented Dialogue System for Industrial Robots". ToD4IR is introduced as a humanized task-oriented dialogue system for industrial robots. The system is designed to assist with manufacturing tasks and enhance user experience. It incorporates fundamentals of small talk and conversation strategies for natural and engaging interactions. The document presents the IRWoZ dataset, which is the first industrial-oriented dialogue corpus. The core algorithm for the dialogue system is likely based on pre-trained language models and transformer architectures, as is common in many modern natural language processing (NLP) applications. Future work includes expanding the IRWoZ dataset to cover more industrial domains and tasks and coherence of dialogues generated by ToD4IR. Finally, the system holds promise for improving human-robot interactions in manufacturing settings through natural and task-oriented dialogue.[24]

The authors of this project are Angel Antonio Martinez-Garate, et al. (2020) are propose the use of Model-Driven Development (MDD) approaches for the creation of conversational agents or chatbot. The project was conducted using a systematic mapping study (SMS) approach which is organized into five stages. The authors applied MDD to conversational agent development by formulating a set of research questions and extracting the data of interest from the articles. The final result of this project is a systematic mapping study (SMS) that provides an overview of the state of the art in the field of conversational agent development process automation using Model-Driven Engineering methodologies. Model-Driven Approaches refer to a software development paradigm that emphasizes the use of models to represent the system being developed.[25]

R. Rajkumar and V. Ganapathy (2022) are proposed a Bio-Inspiring Learning Style Chatbot Inventory using Brain Computing Interface to improve the efficacy of online education. E-learning is the online Learning through the internet. The authors classify the learning styles by conducting two experiments using EEG signals and machine learning. They also implemented VARK questionnaires to classify the learners as introverts or extroverts based on their learning performance. EEG signals are used to analyze the learning styles of individuals and classify them into visual or audio learners. VARK is a learning style inventory that categorizes learners into four different types based on their preferences for visual, auditory, reading or writing and kinesthetic learning. The algorithms used are Naive bayes and J48. Naive bayes is used to classify learners as visual or audio. J48 is a decision tree used for classification and regression. The future work of chatbot is working with AR and VR technologies. This chatbot helps learners to study easy.[26]

The authors of this paper are E.H.-K. Wu et al. (2020) are proposed a hybrid model K-12 E-Learning Assistant Chatbot and discuss its advantages and constraints in E-Learning platforms. The authors propose a chatbot model that combines retrieval-based and generative-based approaches to provide assistance to K-12 students in E-Learning platforms. The chatbot is designed to comprehend and resolve learning-related issues in online education. The retrieval-based model uses a keyword matching algorithm to identify relevant responses from a pre-defined set of responses while the generative-based model uses a neural network to produce replies based on the input query. The authors also use the QANet model for question answering and the SQuAD Evaluation performance for evaluation. SQuAD stands for Stanford Question Answering Dataset which is a sizable dataset for reading comprehension developed by Stanford University to give question-answer pairs. By using this chatbot there will be easy way for education at anytime anywhere.[27]

The author of the paper is John Levi Martin(2023) and the paper explain about ethico-political universe of ChatGPT, an AI tool and the challenges of creating ethical and unbiased AI tools. The paper discusses the attempts to make AI tools "ethical" and "unbiased", and how these attempts can have unintended consequences. The author also examines the underlying model and corpus on which ChatGPT was trained, and analyzes the responses generated by the tool. The paper includes detailed appendices that provide additional information on the methodology used in the investigation. The author also discusses the need for ethical considerations in the development of AI tools and raises important questions about the role of AI in society.[28]

The authors of this project are Kulothunkan Palasundram, et al. (2021) They proposed a multitasking-based Seq2seq model to generate meaningful and relevant answers to the questions given by the user. So to give the answers the authors take eight different models to give answers. In these eight models, they found SEQ2SEQ++ given the most relevant answers and low errors. In this project, different techniques and methods are used by the different models such as global attention mechanism, ternary answer classification to improve the accuracy and relevant answers. The final result is that SEQ2SEQ++ can produce with lower errors and

higher errors on the datasets compared to other models. The advantage of this project is SEQ2SEQ++ model gives more accuracy to questions asked by the users[29]

III. Model Analysis And Discussion

Table 3.1: Comparing Method Accuracy Results

S No	Authors	Methods	Accuracy
1.	Sanjay Chakraborty, Hrithik Paul et al.(2022).	Long-Short Term Memory	94.32%
2.	Vorada Socationurak, Nittayapa Klangpornkun et al.(2021).	Rule-based reasoning, Human supervision	88.89%,
3.	Silvia García-Méndez et al.(2021).	Artificial Intelligence Markup Language, Natural Language Generation	79.99%
4.	Daniel Carlander-Reuterfelt et al.(2020).	SVM is a supervised machine learning	85.37%
5.	Gwendal Daniel,Jordi Cabot,Laurent Deruelle and Mustapha Derras.(2020).	Model Driven Engineering (MDE) techniques,machine learning	90%
6.	Henry Boateng Essel, Anastasios A. Economides et al.(2022).	Quasi-Experimental Design	70%
7.	Antonello Meloni, Simone Angioni et al.(2023).	Quasi-Experimental Design	71.7%
8.	Paula Maddigan And Teo Susnjak.(2023).	Large Language Model(LLM)	71.7%
9.	Kulothunkan Palasundram ,et al.(2023)	Recurrent Neural Network(Rnn),Convolution Neural Network(Cnn)	81%
10.	Martha T. Teye 1, et al. (2022).	Audio-Frame Mean Expression(Afme)	82.59%
11.	E.H.-K. Wu et al. (2020	Retrieval-Based Model,Generative-Based Model	-
12.	John Levi Martin(2023)	Ethical And Political Considerations Surrounding AI	-
13.	Silvia T. Acuna and Oscar Dieste,(2022).	Usability questionnaires,Eye tracking	67.9%
14.	Lenin Medeiros and Tibor Bosse et al.(2022).	Mapping Of Stressors To Support Strategies Used	

The table 3.1 shows the outcomes of a study on the preciseness of different methods. The majority of the studies in the table were conducted in 2020-2023, suggesting that this is an active area of research. There is a wide range of accuracies reported in the table, indicating that there is no single "best" method. The best method for a particular task may depend on the specific data and requirements

Table 3.2: Chatbot Research Paper Insights

S No	Authors	Methodologies And Algorithms	Problems Discussed	Challenges	Future Research Direction
1.	Sanjay Chakraborty, Hrithik Paul Et Al.(2022).	Long-Short Term Memory	1.Lack Of Healthcare 2.Access,Unaffordable Cost	Data Scarcity And Quality, Algorithm Complexity, Security And Privacy	1.Developing Models For More Diseases 2.Improving The Accuracy Of Models 3.Deploy The Model In Real-World Settings
2.	Vorada Socationurak, Nittayapa Klangpornkun Et Al.2021	Rule-Based Reasoning, Human Supervision	1.Access ToJustice, Sensitive Nature Of TheTopic,Accurate 2.Access To Legal Information,Cultural Barrier	1.Acceptance And Adoption, 2.Security And Privacy	1.Developing Chatbots For Different Languages Culture, 2.To Promote Healing
3.	Silvia García-Méndez Et Al.2021	Artificial Intelligence Markup Language, Natural Language Generation	Personalized And Socialized	1.Familiarity In Digital Technologies,Privac 2.Security Concerns	1.More Transparency, Improve Over Time 2.Better User Interfaces
4.	Daniel Carlander-Reuterfelt Et Al.(2020).	Supervised Machine Learning (SVM)	1.Social Presence 2.Imagery Processing	1.Small Sample Size 2.Lack Of Control Over Chatbots	1.Consider The Cultural Context 2.Explore The Role Of Other Factors
5.	GwendaDaniel ,Jordi	Model Driven Engineering	Flexibility,Complexity	Deployment,Time And Cost	1,Improvmnt In Accuracy Of NLU

	Cabot,Laurent Deruelle And Mustapha Derras.2020	(MDE) Techniques,Mac hine Learning			2.Evaluation Of Xatkit In More Domains
6.	Chen Li 1,(Member, Ieee), et al. (2022)	1. Dialogue Management 2. Human-in-the-loop (HITL)	1.Interaction With Industrial Robot 2.Productivity And Safety In The Workplace	1.To Assist With Manufacturing Tasks 2.Incorporates Conversation Strategies	More Industrial Domains And Tasks
7.	Martha T. Teye 1, et al. (2022).	Audio-Frame Mean Expression(Afm e)	1.Ability to detect emotions 2.Actors of culture, context 3.Environment for evaluating	1,Cultural bias 2.Environmental factors 3.Lack of data	More factors of culture, context, environment
8.	Shahid, M. A. Hossain et al. (2022)	Random Forest, Support Vector Machine (Svm),	Comprehensive survey for detecting fake news spreaders.	Fake news spreaders can be human or cyborg that are constantly evolving to avoid detection	New detection methods for adversarial attacks
9.	Yang Ye, Hengxu You And Jing Du.(2023).Proposed	Regular Expression Search Algorithm	1.Trust In Human-Robot Collaboration 2.Miscommunication Between Humans And Robots	1.Robustness 2.Transparency	1.Enabled HRC Systems 2.Developing New Ways
10	Kulothunkan Palasundram ,Et Al.(2023)	Recurrent Neural Network(Rnn) Convolutional Neural Network (CNN)	1. Generic, Meaningless, And Inconsistent Answers.	1.Inability To Deal With Rare Words 2.Language Model Influence	New Training Methods And Datasets
11	Lenin Medeiros And Tibor Bosse Et Al.(2022).	Stressor Mapping to Support Strategies Used by the Proposed Chatbot	Providing Emotional Chatbot To Humans	Whether The Response Is Given Computer Generated Or Human Generated	Including More Stress Features And Giving More Realistic Response To Humans
12	R. Rajkumar And V. Ganapathy (2022)	Naïve Bayes And J Tree Classifier Algorithm(J48)	Chatbot Is Take Long Time To Respond To User Queries Due To Complexity Of Nlp	Less No Of Learners Is Used In The Study,Classification Algorithm Is Depend On The Eeg Signals	Use The Other Psychological Signals,Increase The No Of Learners In The Study,Use Different Machine Learning Algorithms For Better Experience
13	Kulothunkan Palasundram, Et Al. (2021)	Comprehensive Attention Mechanism (CAM),Diverse Loss (DL)	Difficulty In Identifying Input Sequence Such As Parts Of Speech,Generating Repeated Answers	Difficulty In Handling Long Inputs,Generated Answers Which Are Irrelevant To Question	Taking Differnt Datasets In Different Languages To Enhance Chatbot Response
14	Angelo Salatino And Francesco Osborn.(2023)	Support Vector Machine (Svm),	Given Data Have Errors And This Effects The Accuracy And Knowledge Graphs	Ntegrating Data Into Knowledge Graph Require Many Data Formats,Understanding Human Language Queries Is A Big Challenge	Adding The Different Queries Types,Integrating More Data Sources To Develop The Accurate Knowledge Graphs

Chatbot research is an ever-changing field, with many challenges and opportunities. The table 3.2 provides a snapshot of the current state of research, highlighting the key challenges that need to be addressed and the promising directions for future work.

IV. CONCLUSION

In this paper, we have presented a survey on state-of-the-art of chatbots. We have discussed the different types of chatbots, the techniques used in chatbots, and the evaluation results of chatbots. We have also discussed the key findings of the survey, the challenges and limitations of existing chatbots, and the future research directions in chatbots. Overall, chatbots are a promising technology with potential to change the way we engage with computers. However, it is important to be aware of the challenges associated with chatbots and to use them in a responsible way. With the help of educational chatbots, we can provide 24/7

availability, Personalized learning, Proactive support, Reduced costs, and Improved student satisfaction. Educational chatbots using NLP have the ability to transform how we teach and learn. They can provide students with a more customized and efficient learning environment, while also releasing teachers and tutors to concentrate more complex tasks

REFERENCES

- [1] Ali, A. 2001. Macroeconomic variables as common pervasive risk factors and the empirical content of the Arbitrage Pricing Theory. *Journal of Empirical finance*. 5(3): 221–240.
- [2] Basu, S. 1997. The Hill. Jennifer. W. Randolph Ford. and Ingrid G. Farreras. "Real conversations with artificial intelligence: A comparison between human-human online conversations and human-chatbot conversations." *Computers in human behavior* 49 (2015): 245-250.
- [3] Kowalski, Stewart. Katarina Pavlovska. and Mikael Goldstein. "Two case studies in using chatbots for security training." In *Information Assurance and Security Education and Training: 8th IFIP WG 11.8 World Conference on Information Security Education. WISE 8. Auckland. New Zealand. July 8-10. 2013. Proceedings. WISE 7. Lucerne Switzerland. June 9-10. 2011. and WISE 6. Bento Gonçalves, RS, Brazil, July 27-31, 2009, Revised Selected Papers 8*, pp. 265-272. Springer Berlin Heidelberg, 2013.
- [4] Kowalski, Stewart. Katarina Pavlovska. and Mikael Goldstein. "Two case studies in using chatbots for security training." In *Information Assurance and Security Education and Training: 8th IFIP WG 11.8 World Conference on Information Security Education. WISE 8. Auckland. New Zealand. July 8-10. 2013. Proceedings. WISE 7. Lucerne Switzerland. June 9-10. 2011. and WISE 6. Bento Gonçalves, RS, Brazil, July 27-31, 2009, Revised Selected Papers 8*, pp. 265-272. Springer Berlin Heidelberg, 2013.
- [5] Jin, S. Venus. and Seounmi Youn. "Social presence and imagery processing as predictors of chatbot continuance intention in human-AI-interaction." *International Journal of Human-Computer Interaction* 39, no. 9 (2023): 1874-1886.
- [6] Chakraborty, Saniav. Hrithik Paul. Savani Ghatak. Saroi Kumar Pandey. Ankit Kumar. Kamred Udhham Singh. and Mohd Asif Shah. "An AI-Based Medical Chatbot Model for Infectious Disease Prediction." *Ieee Access* 10 (2022): 128469-128483.
- [7] Socratianurak, Vorada. Nittavana Klanornkun. Adirek Munthuli. Phonphan Phienphanich. Lalit Kovudhikulrungsri. Nantawat Saksakulnukorn. Phonkanok Chairaungsri. and Charturong Tantibundhit. "Law-n: Legal guidance through artificial intelligence chatbot for sexual violence victims and survivors." *IEEE Access* 9 (2021): 131440-131461.
- [8] García-Méndez, Silvia. Francisco De Arriba-Pérez. Francisco J. González-Castaño. JOSÉ A. Regueiro-Janeiro. and Feline Gil-Castiñeira. "Entertainment chatbot for the digital inclusion of elderly people without abstraction capabilities." *IEEE Access* 9 (2021): 75878-75891.
- [9] Meloni, Antonello. Simone Angioni. Angelo Salatino. Francesco Osborne. Diego Reforgiato Recunero. and Enrico Motta. "Integrating Conversational Agents and Knowledge Graphs Within the Scholarly Domain." *IEEE Access* 11 (2023): 22468-22489.
- [10] Medeiros, Lenin. Tihor Bosse. and Charlotte Gerritsen. "Can a chatbot comfort humans? Studying the impact of a supportive chatbot on users' self-perceived stress." *IEEE Transactions on Human-Machine Systems* 52, no. 3 (2021): 343-353.
- [11] Ren, Ranci. Mireva Zapata. John W. Castro. Oscar Dieste. and Silvia T. Acuña. "Experimentation for chatbot usability evaluation: A secondary study." *IEEE Access* 10 (2022): 12430-12464.
- [12] Ait-Mlouk, Addi. and Lili Jiang. "KBot: a Knowledge graph based chatBot for natural language understanding over linked data." *IEEE Access* 8 (2020): 149220-149230.
- [13] Carlander-Reuterfeldt, Daniel. Álvaro Carrera. Carlos A. Iglesias. Óscar Araque. Juan Fernando Sánchez Rada, and Sergio Muñoz. "JAICOB: A data science chatbot." *IEEE Access* 8 (2020): 180672-180680.
- [14] Zhang, Lian. Yan Yang. Jie Zhou, Chengcai Chen, and Liang He. "Retrieval-polished response generation for chatbot." *IEEE Access* 8 (2020): 123882-123890.
- [15] Daniel, Gwendal. Jordi Cabot. Laurent Dernelle. and Mustapha Derras. "Xatkit: a multimodal low-code chatbot development framework." *IEEE Access* 8 (2020): 15332-15346.
- [16] Maddison, Paula. and Teo Susniak. "Chat2vis: Generating data visualisations via natural language using chatgpt, codex and gpt-3 large language models." *IEEE Access* (2023).
- [17] Ye, Yang. Hengxu You, and Jing Du. "Improved trust in human-robot collaboration with ChatGPT." *IEEE Access* (2023).
- [18] Meloni, Antonello. Simone Angioni. Angelo Salatino. Francesco Osborne. Diego Reforgiato Recunero. and Enrico Motta. "Integrating Conversational Agents and Knowledge Graphs Within the Scholarly Domain." *IEEE Access* 11 (2023): 22468-22489.
- [19] Chen, Tzu-Yu. Yu-Ching Chin. Nanvi Bi. and Richard Tzong-Han Tsai. "Multi-modal chatbot in intelligent manufacturing." *IEEE Access* 9 (2021): 82118-82129.
- [20] Santos, Giovanni Almeida. Guilherme Giv de Andrade. Geovana Ramos Sousa Silva. Francisco Carlos Molina Duarte. João Paulo Javidi Da Costa. and Rafael Timóteo de Sousa. "A conversation-driven approach for chatbot management." *IEEE Access* 10 (2022): 8474-8486.
- [21] Shahid, Waiha. Yiran Li. Dakota Staples. Gulshan Amin. Saqib Hakak. and Ali Ghorbani. "Are you a cyborg, bot or human?—a survey on detecting fake news spreaders." *IEEE Access* 10 (2022): 27069-27083.
- [22] Palasundram, Kulothunkan. Nurfadhilina Mohd Sharef. Khairul Azhar Kasmiran. and Azreen Azman. "Enhancements to the sequence-to-sequence-based natural answer generation models." *IEEE Access* 8 (2020): 45738-45752.
- [23] Teve, Martha T. Yaw Marfo Missah. Emmanuel Ahene. and Twum Frimpong. "Evaluation of conversational agents: understanding culture, context and environment in emotion detection." *IEEE Access* 10 (2022): 24976-24984.
- [24] Kansar, Soufia. Bilal Tahir. and Muhammad Amir Mehmood. "Push-to-Trend: A Novel Framework to Detect Trend Promoters in Trending Hashtags." *IEEE Access* 10 (2022): 113005-113017.
- [25] Li, Chen. Xiaochun Zhang. Dimitrios Chrysostomou. and Hongji Yang. "Tod4ir: A humanised task-oriented dialogue system for industrial robots." *IEEE Access* 10 (2022): 91631-91649.
- [26] Raikumar, R., and Velanna Gananath. "Bio-inspired learning style chatbot inventory using brain computing interface to increase the efficiency of e-learning." *IEEE Access* 8 (2020): 67377-67395.
- [27] Wu, Eric Hsiao-Kuang. Chun-Han Lin. Yu-Yen Ou. Chen-Zhong Lin. Wei-Kai Wang. and Chi-Yun Chao. "Advantages and constraints of a hybrid model K-12 E-Learning assistant chatbot." *Ieee Access* 8 (2020): 77788-77801.
- [28] Martin, John Levi. "The Ethico-Political Universe of ChatGPT." *Journal of Social Computing* 4, no. 1 (2023): 1-11.
- [29] Palasundram, Kulothunkan. Nurfadhilina Mohd Sharef. Khairul Azhar Kasmiran. and Azreen Azman. "SEO2SEO++: A multitasking-based Seq2Seq model to generate meaningful and relevant answers." *IEEE Access* 9 (2021): 164949-164975.
- [30] Liu, Bingquan. Zhen Xu. Chengjie Sun. Baoxun Wang. Xiaolong Wang. Derek F. Wong. and Min Zhang. "Content-oriented user modeling for personalized response ranking in chatbots." *IEEE/ACM Transactions on Audio, Speech, and Language Processing* 26, no. 1 (2017): 122-133.

- [31] Kubiak. Patrick, and Stefan Rass. "An overview of data-driven techniques for IT-service-management." IEEE Access 6 (2018): 63664-63688.
- [32] Sánchez-Adame. Luis Martín. Sonia Mendoza. José Urquiza. José Rodríguez. and Amilcar Meneses-Viveros. "Towards a set of heuristics for evaluating chatbots." IEEE Latin America Transactions 19, no. 12 (2021): 2037-2045.
- [33] Lam. Khanh Nhut. Loc Huu Nong, and Jugal Kalita. "A Transformer-based Educational Virtual Assistant Using Diacriticized Latin Script." IEEE Access (2023).
- [34] Abdellatif. Ahmad. Khaled Badran. Diego Elias Costa. and Emad Shihab. "A comparison of natural language understanding platforms for chatbots in software engineering." IEEE Transactions on Software Engineering 48, no. 8 (2021): 3087-3102.
- [35] Cai. Wanling. Yucheng Jin. and Li Chen. "Task-Oriented User Evaluation on Critiquing-Based Recommendation Chatbots." IEEE Transactions on Human-Machine Systems 52, no. 3 (2022): 354-366.
- [36] Srivastava. Binlav. Francesca Rossi. Sheema Usmani. and Mariana Bernagozzi. "Personalized chatbot trustworthiness ratings." IEEE Transactions on Technology and Society 1, no. 4 (2020): 184-192.
- [37] Liu. Bingquan. Zhen Xu. Chengjie Sun. Baoxun Wang. Xiaolong Wang. Derek F. Wong. and Min Zhang. "Content-oriented user modeling for personalized response ranking in chatbots." IEEE/ACM Transactions on Audio, Speech, and Language Processing 26, no. 1 (2017): 122-133.
- [38] Denecke. Kerstin. Savan Vaaheesan. and Aaganva Arulnathan. "A mental health chatbot for regulating emotions (SERMO)-concept and usability test." IEEE Transactions on Emerging Topics in Computing 9, no. 3 (2020): 1170-1182.
- [39] Nordheim. Cecilie Bertinussen. Ashjørn Følstad. and Cato Alexander Bjørkli. "An initial model of trust in chatbots for customer service—findings from a questionnaire study." Interacting with Computers 31, no. 3 (2019): 317-335.
- [40] Gu. Jia-Chen. Zhen-Hua Ling. and Ouan Liu. "Utterance-to-utterance interactive matching network for multi-turn response selection in retrieval-based chatbots." IEEE/ACM Transactions on Audio, Speech, and Language Processing 28 (2019): 369-379.
- [41] Firdaus. Manaiama. Arunav Shandilva. Asif Ekbal. and Pushpak Bhattacharvya. "Being polite: Modeling politeness variation in a personalized dialog agent." IEEE Transactions on Computational Social Systems (2022).
- [42] Zhang. Chen. Luis Fernando D'Haro. Qiuan Zhang. Thomas Friedrichs. and Haizhou Li. "PoE: A Panel of Experts for Generalized Automatic Dialogue Assessment." IEEE/ACM Transactions on Audio, Speech, and Language Processing 31 (2023): 1234-1250.
- [43] Hu. Jiaxing. Yun Huang. Xiaozhu Hu. and Yingqiao Xu. "The acoustically emotion-aware conversational agent with speech emotion recognition and empathetic responses." IEEE Transactions on Affective Computing 14, no. 1 (2022): 17-30.
- [44] Yang. Yaoli. Weizheng Wang. Zhimeng Yin. Renhui Xu. Xiaokang Zhou. Neeraj Kumar. Mamoun Alazab. and Thinna Reddy Gadikaluri. "Mixed game-based AoI optimization for combating COVID-19 with AI bots." IEEE Journal on Selected Areas in Communications 40, no. 11 (2022): 3122-3138.
- [45] Klonfenstein. Lorenz Cuno. Saverio Delbriori. Silvia Malatini. and Alessandro Bogliolo. "The rise of bots: A survey of conversational interfaces, patterns, and paradigms." In Proceedings of the 2017 conference on designing interactive systems, pp. 555-565. 2017.
- [46] Xu. Anbang. Zhe Liu. Yufan Guo. Vibha Sinha. and Rama Akkirai. "A new chatbot for customer service on social media." In Proceedings of the 2017 CHI conference on human factors in computing systems, pp. 3506-3510. 2017.
- Investment Performance of Common Stocks in Relation to their Price to Earnings Ratio: A Test of the Efficient Markets Hypothesis. Journal of Finance, 33(3): 663-682.
- [3] Bhatti, U. and Hanif. M. 2010. Validity of Capital Assets Pricing Model.Evidence from KSE-Pakistan.European Journal of Economics, Finance and Administrative Science, 3 (20).