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Talking Machine: A Survey of Chatbot Foundation, Use Case, and Challenges

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ABSTRACT

Recently, chatbot systems have grown from the very basic rule-based systems to more advanced ones, such as natural and context-aware systems that incorporate sophisticated neural network techniques. This paper provides a comprehensive review of evolution and taxonomy and analyzes the application of chatbots in various fields, such as healthcare, banking, education, mental health, customer service, and image recognition, to reveal contemporary strengths and applications. In addition to observation of the most important assessment measurements and highlights of the latest studies, promising performance has been reported in the literature, with accuracy/success rates over 90% for some studies, with user satisfaction levels reaching 95% in certain health-related scenarios; however, these results remain specific to their settings rather than generalizable for all chat applications. The paper concludes that contemporary AI-based chatbots are strong in response generation and context appreciation but are still weak when dealing with ambiguous questions and multi-turn dialogues. Some of the key challenges, such as making the system scalable and personal and achieving human-like conversational quality in different contexts, were identified. This in-depth review summarizes recent developments as well as challenges in the area of chatbot technology and emphasizes the necessity of innovation in AI and NLP to overcome these challenges and improve chatbot performance and user experience.

1. INTRODUCTION

The development and application of the chatbot system have seen significant progress, which is inspired by Artificial Intelligence (AI), integration of Machine Learning (ML) and natural language treatment. These systems are designed to follow human conversations, offering a series of functionalities ranging from work -oriented interactions to open dialogues. The development of chatbots is characterized by a change in the refined neural network -based approaches more than the rule -based model, which increases their ability to understand and generate human reactions. This review examines different models, applications and evaluation techniques used in modern chatbot systems, which highlight their ability and challenges. Chatbots are mainly controlled and classified in neural network -based models. Rule-based systems are reliant on pre-defined templates that are well suited for simple interactions that have a task-oriented purpose while neural network-based models and systems are better suited for more complex, out-of-domain conversations [1] Moreover, current chatbot implementations, including DeepProbe and AliMe, utilize modern architectural approaches that are associated with knowledge domains, response generation and ML models to increase interaction [2] Furthermore, the trend is towards developing knowledge-based models that leverage AI to positively affect both chatbot intelligence and user experience [3]. Chatbots can be broadly categorized into four different types: rule-based systems, retrieval-based systems, generative systems, and hybrid systems. The architecture begins with an

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input from the user followed by steps including natural language processing, intent identification, dialogue state management, and finally, output generation with the goal of providing an output to the user. Chatbots can be used for Frequently Asked Questions (FAQ) systems, customer service systems, health triage systems, education systems, and much more, Furthermore chatbots have come a long way from their rule-based counterparts in the 1960s named ELIZA, then came the retrieval-based models, till now with more advanced forms of generative systems that allow for more natural flows in conversation[2], [6]. We can observe implemented applications of chatbots across a variety of domains, for example, the healthcare sector is increasingly implementing chatbots with mental health support and medical education. In these examples, research is limited, but they seem to show promise in their respective areas, meaning more research is needed to support effectiveness [4].The service industry has benefited from the application of chatbots because they can provide very efficient and low-cost customer service with models based on query understanding and response generation [5]. Evaluating a chatbot could also depend on parameters such as question-answering capability and the ability to produce appropriate output responses. There have been some encouraging outcomes demonstrated in different fields using these approaches, but these capabilities happen to be highly dependent on the specific usage of these chat bots [1]. The next level in the development of a chat bot is likely to rely on improvement in neural net architecture designs using new approaches in the field of AI [2], [5]. Though promising prospects that chatbots possess for various application domains are accompanied by despite several issues in achieving human-like interaction quality as well as guaranteeing their efficacy for complex scenarios. Future developments of AI and ML hold utmost significance for addressing these issues and to fully leverage chatbot system potential [6]. The remainder of this paper is organized as follows: Section 2 reviews chatbot applications across multiple domains, Section 3 outlines future research directions, and Section 4 concludes the paper. This review followed a structured survey protocol. The search for studies between 2018-2025 in IEEE Xplore, Scopus, Springer, and Google search using search terms such as “chatbot,” “conversational agent,” and “dialog system,” with peer-reviewed sources that focused on models, applications, or evaluations of chatbots being included in the study, with duplicates, sources in languages other than English, and opinion pieces using technical terminology being excluded from the survey.

2. Review of Previous Studies

The progress of AI, machine learning, and Natural Language Processing (NLP) technologies, and the implementation of neural and transformer-based models in chatbots, let them efficiently operate in customer assistance, education, and telehealth sectors. Automating speech and making interactions more meaningful is made possible due to the chatbots’ NLP capabilities and neural models. While the usage of chatbots is widespread, challenges such as privacy, ethical concerns, and scalability issues have become commonplace. The absence of literature examining the technical and deployment obstacles of chatbot technologies further develops the goal of this literature review.

2.1 Healthcare Sector

Symptoms of the chatbot system change the health care system by providing AI-operated assistance immediately, contract planning and patient assistance. Their integration increases access, reduces the charge of medical personnel, and the patient improves the engagement. Aparna et al. presented a web-based chatbot using Dialogflow in the healthcare domain. This system helped to digitize the hospital workflow, such as scheduling appointments and information related to doctors. It also had a Flask backend to handle data from the database (MySQL). The experimental results were 92% response accuracy and 99% success rate in appointment booking. The system was limited in multi-intent and open-ended queries [7]. While Dalavai et al. used Google Translate's Application Programming Interface (API), coupled with an NLP pipeline, to enable multilingual medical support, the chatbot achieved 87% accuracy on a multilingual medical dataset. Translation errors, particularly in clinical terminology, were a notable limitation [8]. Moreover, another method introduced the Bidirectional Encoder Representations from Transformer (BERT) model for semantic parsing and integrated it with Google's Speech-to-Text API. The chatbot achieved 91% voice input accuracy across various intents. It performed well in quiet environments but degraded under noisy conditions [9]. Besides that, Shaikh et al. focused on reaching remote users with limited access to medical professionals. The chatbot used local language processing and decision trees for triage. It had a resolution success of 82% in rural pilot tests but required better network stability [10]. Also, Benita et al. developed an emergency chatbot using NLP, decision trees, and location tracking to deliver quick medical guidance. It reached 90% accuracy in symptom recognition but had trouble with complex or multi-layered medical cases [11]. As well as Furqan et al. introduced a medical chatbot that guides users in identifying possible illnesses based on symptom input. The system is built using NLP and decision trees; the system can also pull information from online sources when its internal database falls short. It performed well in identifying conditions like vertigo and diabetes, offering additional related symptoms to enhance understanding. Although the system proved helpful in remote communities, its ability to handle more complicated or overlapping cases was not thoroughly measured [12]. Finally, Rainey et al. evaluated a chatbot used to support patients after Periacetabular Osteotomy (PAO). The chatbot automatically provided daily check-in and recovery guidance, achieved 95.4% total satisfaction, and helped reduce the patient's anxiety in improvement. However, it provided limited adaptation to the needs of an individual patient and did not replace traditional medical conversation [13].

2.2 Banking and Business Support

The support of banking and businesses through the use of chatbot systems has emerged as a novel means for the improvement of customer service and efficiency of business. The use of these systems enables customers to have continuous support from the systems at all times of the day and night. Despite the benefits of these systems, challenges such as security of data and acceptance by customers have emerged as significant factors that inhibit the adoption of the systems. The rule-based system was designed for the automation of structured banking queries with a 90% accuracy rate for transactional queries and provides continuous support for banking services. The system is ineffective in handling ambiguous queries or queries that are unstructured in nature [14]. Field testing revealed an 84% success rate in addressing customer queries. Although effective, the system lacked deeper contextual awareness and ML adaptability [15]. In addition to that new customer service chatbot integrated with ML, it applied a supervised learning model using Naive Bayes (NB) to categorize customer questions; the model achieved 93% accuracy on labeled datasets, and it was strong at repetitive queries but weak on ambiguous or rare inputs [16]. Rodriguez et al. also evaluated the capability of chatbot platforms in e-commerce using descriptive statistics and structured questionnaires to capture data from users. Research authors reported a satisfaction rate of 89% and indicated good responsiveness and availability around the clock. In addition, the authors stated that it was a very limited ability to make personal reactions and complex inquiries [17]. In addition, a long -term short -term memory (LSTM) -based emotional analysis model examined customer perception of service chatbots during online shopping experiences. The model reached 88% accuracy in terms of classifying the user's spirit as positive, neutral or negative. Emotional analysis provided great benefits, including the use of different methods to analyze customers' response in real time and better service insight. However, a specific emotional response had a specific and reference dependent query [18].

2.3 Education and Academic Support

Chatbot technologies have become a disruptive learning technology, particularly in a college/academic support context. It's facilitation of communication efficiently between educational institutions and students, also proving to be of use in many ways (i.e., in an administrative manner and through helping students through specially created chatbots for students). Safwa et al. created a Dialogflow-based chatbot to respond to queries in the context of college through the use of FastAPI and MySQL that was 99% accurate in principal areas (admission and courses). The chatbot was helpful in reducing the staff's workload and offered immediate support to students. The chatbot did not take advantage of multilingual support nor display contextual assessment sophistication [19]. Additionally, another study used NLP and Python to build an educational chatbot that achieved an accuracy of 92% in answering routine questions and decreased the workload of the staff by automating the support process. However, it simply did not have the depth to perform on vague queries or queries with multiple intentions [20]. In addition, Mahant et al designed a student support chatbot built on Python's Django framework and spaCy for NLP. , the chatbot provided accurate responses and decreased the staff workload, although it did not include voice capabilities and multilingual functionality [21]. Moreover, Kondreddy et al. suggest a new system based on advanced NLP techniques with the Natural Language Toolkit (NLTK) library and neural networks; the suggested model achieved 99% accuracy. The system provided real-time, context-aware responses through intent classification, verbal parsing, and a bag-of-words model. While highly effective, future improvements may be needed to better handle complex, domain-specific queries [22]. Besides that, the new method applied a decision tree model to suggest suitable colleges based on user profiles. The model achieved 86% match accuracy. The study noted bias in dataset sourcing [23]. Also, Patil & Dhiman developed a web-based FAQ chatbot using JavaScript and Flask. Test results showed a 79% answer accuracy. Weaknesses encompassed reliance on a static database [24]. A rule-based logic tree is a different method employed to help high school students via stream selection. The model acquired 90% accuracy in guiding. but Restricted scalability resulting from handwritten logic design [25].

2.4 Mental Health and Emotional Support

Recent researches show that chatbots help users manage their mental well-being by holding personalised conversations. Chatbots use NLP and ML technologies to provide guidance, emotional middle intervention, and check-ins. The users feel that their mental well-being is monitored and supported by the chatbots, and the mental health care professionals also have insight into users' mental health outside the clinical settings. Kondhalkar achieved 94% accuracy by using text-only methods to detect emotions through the patterns of emotional data and emotional data labelling. Yet it struggles and cannot detect mixed emotions, unclear feelings, and non-text components. [26]. While Singh et al works combine the detection of facial emotions with the large language models (LLMs) to facilitate the invention of emotionally aware conversations. He reported achieving 91% accuracy in the matching of users and emotions to the system’s responses. The system’s responses improved the interactions in real time. The system, however, lacked depth in complex dialogues, and it could not respond to unpredictable inputs [27]. Moreover, Huang et al. performed a scoping review covering 27 papers to assess the impact of chatbots on student motivation within educational institutions. Their study revealed that well-designed chatbots, using personalized and interactive features, can enhance engagement, autonomy, and positive learning outcomes. The analysis highlighted the inconsistent testing techniques employed by researchers in assessing motivation and the absence of long-term researches on motivation outcomes as limitations.[28].

2.5 Customer Service and Technical Applications

Chatbots are changing customer service and tech support for the better by improving efficiency. They also improve customer satisfaction and support them at any time of the day. They drive the automation of routine inquiries. Customers get timely responses, and human agents can focus on complex inquiries. This improves overall operational efficiency. Huang et al. described a multilingual chatbot ticketing system utilizing Tensorflow and LLMs with Quick Response (QR) code integration for access. Although no accuracy metrics were given, the system demonstrated operational efficiency, yet poor scalability and understanding of emotions during peak demand [28]. A different focus on integration and web cross functionality, including password reset, used Python-Flask and an HTML frontend. They demonstrated a response rate of 89%, yet no learning functionality was present [29]. Also, An additional method described was an offline chatbot with a preloaded list of FAQs, useful for locations with limited connectivity. This suggestion achieved a 75% match precision although a small database was a major detriment [30]. Moreover, the Knuth-Morris-Pratt algorithm for query string pattern matching provided 82% accuracy but was not adaptable to informal language or other slang [31]. On the contrary, Shekgola et al. presented a conceptual framework of how AI chatbots could facilitate society toward Smart Government. Although the system showed great potential in enhancing and automating citizen engagement, there is no quantitative measurement or hands-on showing of the effectiveness of real-world deployment [32]. Puspitasari et al. developed an NLP-based virtual assistant including tokenization and lemmatization. It has enhanced user engagement, and responses have not been tested for their accuracy on an ambiguous or varied set of user input [33]. Klamath built the chatbot using prescriptive rules and NLP tools. They used Dialogflow NLU technologies; The system improved customer support by automatically providing customized responses, but it had the problem of unclear input data and made people concerned about their data security and trust [34]. Finally, Kagan et al. conducted a study of real-world customer chatbot deployments, highlighting significant obstacles such as Clint hesitation and poor previous experiences .they suggested solutions like pre-chat disclaimers and optional human handover in order to increase user acceptance. [35].

2.6 Image Recognition and Specialized Domains

The integration of chatbots with image recognition technologies has led to support in multiple fields such as medical diagnosis and smart monitoring. By combining visual entrance analysis with natural language interaction. A proposed method merged NLP with image processing using OpenCV and TensorFlow, the accuracy achieved was 88%, but it still faced difficulties with poor image resolution [36]. Another method worked as an educational tool using image query inputs, Leveraged MobileNet and Flask. the accuracy achieved was 86%, while limitations exist by dependency on model training set size [37]. In addition, Adharsh et al. suggest a restaurant-focused chatbot using NLTK to automate customer inquiries. While the system improved order processing and assisted customers with menus, it lacked formal accuracy testing and had difficulty recognizing slang terms or ambiguous input. [38].

Tables below provide a clear comparative understanding of the Chatbot study that has been reviewed in various fields. This table models or techniques are used, and uses the application domain, reported performance measurements, as well as the strengths and weaknesses of each approach. Such a synthesis allows readers to identify technical trends, sector -specific performance and frequent challenges.

Table 1: Healthcare Chatbots

Study	Model / Technique	Task	Performance	Strengths	Weaknesses
Aparna et al. (2025) [7]	Dialogflow + Flask + MySQL	Healthcare – hospital workflow	92% accuracy, 99% booking success	Automated scheduling, improved workflow	Weak in multi-intent queries
Dalavai et al. (2025) [8]	Google Translate API + NLP pipeline	Healthcare – multilingual support	87% accuracy	Multilingual capability	Errors in medical terminology

Study	Model / Technique	Task	Performance	Strengths	Weaknesses
M.E.K. (2025) [9]	BERT + Speech-to-Text	Healthcare – voice input	91% accuracy (quiet env.)	Contextual accuracy	Drops in noisy environments
Shaikh, Furqan, Benita (2023–2025) [10–12]	**NLP + Decision Trees** (merged)	Healthcare – triage, symptom checking, emergencies	82–90% accuracy	Effective in rural/remote/emergency	Limited for complex/multi-layered cases
Rainey et al. (2025) [13]	Automated daily check-in bot	Healthcare – post-surgery recovery	95.4% satisfaction	Reduced anxiety, strong patient support	Limited personalization

Table 2: Banking and Business Chatbots

Study	Model / Technique	Task	Performance	Strengths	Weaknesses
S.M. (2025) [14]	Rule-based model	Banking – transactions	90% accuracy	Reliable 24/7 responses	Weak for ambiguous queries
Yadav (2025) [15]	Flask + MySQL + keyword match	Agrochemical sector	84% success	Effective handling	No contextual depth
Thrimoorthy (2025) [16]	Naive Bayes	Banking – customer service	93% accuracy	Good repetitive queries	Weak rare/ambiguous queries
Rodriguez et al. (2025) [17]	Generic chatbot survey	E-commerce / banking	89% satisfaction	Responsive bots	Poor personalization
Lakkangoudra (2025) [18]	LSTM sentiment analysis	E-commerce service bots	88% accuracy	Real-time sentiment	Weak nuanced emotions

Table 3: Education Chatbots

Study	Model / Technique	Task	Performance	Strengths	Weaknesses
Safwa, Chitra, Mahant, Kondreddy (2025) [19–22]	Dialogflow / spaCy / NLTK NN (merged)	Education – student support, info	92–99% accuracy	Reduced staff workload, real-time	Limited multilingual/voice
Padmavathi (2025) [23]	Decision Tree model	Education – college recommendation	86% accuracy	Guides student choices	Dataset bias
Patil & Dhiman (2025) [24]	Flask + JavaScript FAQ	Education – portal chatbot	79% accuracy	Fast responses	Static DB
Abinaya (2025) [25]	Rule-based logic tree	Education – high school guidance	90% accuracy	Career guidance	Limited scalability

Table 4: Mental Health and Emotional Support Chatbots

Study	Model / Technique	Task	Performance	Strengths	Weaknesses
Kondhalkar (2025) [26]	Text-only emotion detection	Mental health – chatbot	94% accuracy	Matches training data	Weak mixed feelings
Singh (2025) [27]	Facial recognition + LLMs	Mental health – emotion-aware	91% accuracy	Real-time emotion	Struggles unpredictable input

Table 5: Customer Service and Technical Applications Chatbots

Study	Model / Technique	Task	Performance	Strengths	Weaknesses
Huang et al. (2025) [28]	TensorFlow + LLMs + QR	Customer service – multilingual ticketing	Operational efficiency	Strong multilingual	Scalability issues
Venkatchalam (2025) [29]	Flask + HTML	Customer service – ticketing	89% response	Smooth integration	No self-learning
Karande (2025) [30]	Offline FAQ	Customer service	75% precision	Works offline	Limited DB
Christian & Erline (2022) [31]	Knuth-Morris-Pratt algo	Customer queries	82% accuracy	Efficient matching	Weak with slang
Shekgola (2025) [32]	AI Smart Gov chatbot	Citizen interaction	Qualitative	Improves e-gov	No metrics
Puspitasari (2024) [33]	NLP (tokenization, lemmatization)	Virtual assistant	Qualitative	Better engagement	No accuracy testing
Kalmath (2024) [34]	Dialogflow NLU	Customer help	Qualitative	Customized replies	Trust issues
Kagan (2025) [35]	Adoption survey	Customer service	Qualitative	Insights on adoption	No evaluation

Table 6: Image Recognition and Specialized Domains Chatbots

Study	Model / Technique	Task	Performance	Strengths	Weaknesses
Augustine (2025) [36]	NLP + OpenCV + TensorFlow	Image recognition chatbot	88% accuracy	Strong NLP-image link	Poor resolution handling
Khachane (2025) [37]	MobileNet + Flask	Image-based chatbot (education)	86% accuracy	Effective image queries	Dependent on dataset
Adharsh (2025) [38]	NLTK chatbot	Restaurant orders	Qualitative	Improved order handling	Weak with slang

3. Future Direction

In the future, the chatbot system is expected to develop into complex, reference-free interactions and more comfortable and emotionally developed intelligent devices. Research will focus on the user's recognition to recognize and improve their ability to react sympathetically while at the same time seeming interactions through advanced personalization techniques. Multilingual and culturally adaptive systems will be necessary, especially in global fields such as health care and education. Data will also impact the Centre for Privacy and the Moral Idea Centre, as these systems are more advanced in relation to user trust. Things such as melding with new technologies like IoT and augmented reality, and expanding upon their capabilities. Chatbots will need a scalable and flexible structure to meet the rise in demand. In a nutshell, chatbots will become integrated into the everyday life of users, and their function will be shifted from just a basic automated responder to advanced assistants.

4. Conclusion

The previous studies reflect the great progress achieved by chatbot systems in domain-specific tasks, particularly within a structured environment where both interaction patterns and user intent are clear. Across different industry verticals like health care, education, banking, and customer services, the numerous studies confirmed high accuracy and user acceptance, but these are mainly based on policed task environments and a limited conversational range.. However, in situations where chatbot systems are faced with the challenges of unclear user input, longer conversations, and multi-intent interactions, the phenomenon of performance degradation is a recurring theme. Moreover, the study reveals that the difficulties associated with the aspects of contextual integrity, the level of personalization, the concerns of ethics, and the privacy of data are still prevalent in the majority of the application domains.

Conflicts of Interest

The authors declare no conflicts of interest.

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