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Systematic analysis of communicative efficiency between rule-based chatbots and natural language models

Análisis sistemático sobre la eficiencia comunicativa entre chatbots basados en reglas y modelos de lenguaje natural

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Abstract

The study was grounded in a systematic literature review on the communicative efficiencies of rule-based conversational agents and those powered by natural language models with artificial intelligence. A total of 175 documents were analyzed as the basis for this review. Additionally, a historical analysis of the first recorded conversational agent, ELIZA, developed in 1966, was included, highlighting its pivotal role in the emergence of rule-based systems. The study also delved into the arguments underpinning the significant differences between rule-based conversational agents and those leveraging natural language models. These differences revealed that rule-based systems are simple and cost-effective tools, ideal for repetitive and structured tasks, yet constrained in managing complex interactions. Conversely, agents powered by natural language models enable more adaptive and personalized interactions, albeit requiring substantial investment in data and development.

According to the findings, the choice between these approaches depends on the application context, available resources, and the specific needs of the organization. Furthermore, the research underscored the evolution of conversational agents and their transformative impact across various sectors. In this regard, the results open pathways to explore how emerging technological trends, such as advanced natural language processing models, can enhance the efficiency and applicability of these systems while addressing the ethical and technical challenges associated with their implementation in diverse industries.

Keywords

Chatbots, natural language processing, communication, artificial intelligence, NLP.

Resumen

El estudio se fundamentó en una revisión sistemática de la literatura sobre las eficiencias comunicativas de los chatbots basados en reglas y aquellos basados en modelos de lenguaje natural con inteligencia artificial. Se analizaron 175 documentos como base para esta revisión. También se incluyó una breve historia del primer chatbot registrado, denominado ELIZA en 1966, que dio paso al desarrollo de los chatbots basados en reglas. Además, se profundizó en los argumentos que sostienen las notables diferencias entre los chatbots basados en reglas y los basados en modelos de lenguaje. En ese sentido, se revelaron diferencias significativas entre ambos tipos. Los sistemas basados en reglas son herramientas simples y económicas, óptimas para tareas repetitivas y estructuradas, pero limitadas para manejar interacciones complejas. Mientras que los asistentes impulsados por modelos de lenguaje natural ofrecen interacciones más adaptativas y personalizadas, aunque requieren una inversión significativa en datos y desarrollo. De acuerdo al estudio, la elección entre ambos enfoques depende del contexto de aplicación, los recursos disponibles y las necesidades específicas de la organización. Además, los resultados evidencian la evolución de los asistentes conversacionales y su impacto en diversos sectores, en ese sentido, los resultados permiten explorar cómo las tendencias tecnológicas emergentes, como los modelos avanzados de procesamiento de lenguaje natural, pueden ampliar la eficiencia y la aplicabilidad de estos sistemas, enfrentando a la vez desafíos éticos y técnicos asociados con su implementación en diversas industrias.

Palabras clave

Chatbots, procesamiento del lenguaje natural, comunicación, inteligencia artificial, PLN.

Introduction

Chatbots, also known as virtual assistants, have evolved significantly since their inception, moving from simple rules-based programs to sophisticated systems driven by natural language models. This evolution has been driven by advances in artificial intelligence (AI) and natural language processing (NLP), which has allowed conversational attendees to interact more effectively and naturally with users (Joulin, 2017).

The size of the virtual assistant market is growing rapidly, from $250 million in 2017 to more than $1.34 billion in 2024 (MarketsandMarkets, 2020). More than 21 % of adults in the United States and more than 80 % of Gen Z use voice/text bots for information search and shopping (Pew Research Center, 2022). Many brands, such as American Eagle Outfitters and Domino's Pizza, have implemented chatbots to take orders or recommend products, and major platforms such as Amazon, eBay, Facebook, and WeChat have adopted chatbots for conversational commerce (Luo *et al.,* 2019).

With the ChatGPT foray launched by OpenAI in November 2022, the size of the conversational agent user market soared. According to data from Silverio (2024), as of November 2023, the number of users of ChatGPT was 180.5 million globally, and the number of visitors to its page reached 1.626 million in February 2024.

This study presents a systematic literature review on the foundations and communicative efficiency of conversational assistants based on predefined rules and those designed by natural language models with AI. The review was based on the analysis of 175 academic documents and considered, in addition, a historical perspective by including ELIZA, the first system registered in 1966, which laid the foundations for systems structured in rules.

In addition, the analysis delves into the key differences between conversational assistants designed under rules and those driven by natural language models. Rule-based systems were identified as simpler and more economical, albeit limited, solutions for managing complex human interactions. On the other hand, systems based on natural language models proved to be more adaptive and natural in their interactions, although their development requires significant investment and large volumes of data.

The choice between these systems depends on the needs and resources of the organization. The main findings highlighted the evolution, benefits and disadvantages of both types of virtual assistants, providing a basis for future research and practical applications in various industries.

Evolution and rule-based chatbot technologies

A rule-based virtual assistant, also known as a decision tree virtual assistant, uses a predefined set of rules to handle interactions with users. These rules are based on specific keywords or patterns in user communication and are organized in a similar way to a flowchart to anticipate potential questions and provide appropriate answers (Dale, 2020).

According to a Hubtype (2023) article, these conversational assistants are easier to build and maintain compared to artificial intelligence-based chatbots. They do not require continuous learning, making them faster and cheaper to implement. However, they are limited to the scenarios for which they were programmed and cannot handle questions outside of their predefined rules.

Another source highlights that rules-based conversational agents are common in applications where interactions are predictable and repetitive, such as in customer service or FAQ systems. These chatbots cannot learn from new interactions or communications, limiting their ability to handle more complex or dynamic conversations (Caldarini *et al.,* 2022).

According to Caldarini *et al.* (2022), searches are performed on databases such as IEEE, ScienceDirect and Springer using terms related to virtual assistants to identify relevant articles. Areas addressed include Natural Language Processing (NLP) and Artificial Intelligence (AI). In addition, repositories such as arXiv, Google Scholar and JSTOR are explored, where 62,254 relevant publications on these topics are selected.

Rules-based conversational assistants, due to their simplicity, are preferred in situations where a quick and economical solution is required. However, their inability to adapt to new situations limits their effectiveness in dynamic environments (Pradella, 2016).

In contrast, virtual assistants based on natural language models, although more complex and expensive, offer greater adaptability and ability to handle unforeseen interactions, making them ideal for more advanced and demanding applications (Dale, 2020).

History and development of the first chatbots

Early virtual assistants, such as ELIZA, created by Joseph Weizenbaum in the 1960s, relied on predefined rules to simulate a human conversation. ELIZA used predefined keyword patterns and responses to interact with users, allowing it to hold basic conversations, although it lacked the ability to understand the context or intent behind the user's words (Weizenbaum, 1966).

Reviewing its history, ELIZA was a program developed at MIT that allowed the first natural language interaction between a human and a computer. Operating on the MAC timesharing system, ELIZA analyzed input sentences based on keyword-triggered decomposition rules and generated responses using reassembly rules (Weizenbaum, 1966).

ELIZA's main goal was to explore how computers can simulate human conversations using predefined rule structures. These systems were limited and predictable, suitable only for simple tasks and predefined dialog structures (Shawar and Atwell, 2007).

ELIZA simulated a conversation using a pattern matching and substitution methodology that gave users the illusion of understanding, although it lacked an integrated framework for contextualizing events (Weizenbaum, 1966; Goldman, 2017). Pattern matching is a key methodology in the development of rules-based virtual assistants. This approach focuses on identifying specific patterns in user input to generate predefined responses (Goldman, 2017).

One of the notable contributions in Weizenbaum's (1966) study was that ELIZA managed to maintain a coherent conversation, largely dependent on the assumptions and rationalizations the user made about the program's capacity. Users tended to attribute understanding and knowledge to the program, filling in the gaps with their own imagination and expectations. Weizenbaum (1966) also mentions the possibility of conducting experiments to explore the extent to which users can be convinced that they are interacting with a human rather than a machine. This leads to the famous "Turing Test", where the goal is that a user cannot distinguish between a conversation with a human and one with a machine. The credibility of ELIZA's responses is crucial to maintain this illusion.

In Weizenbaum's study (1966), it is noted that ELIZA is able to create the illusion that she understands the user's input, although she does not really understand the context or intention behind the words. This is achieved through responses generated by predefined rules that seem pertinent to the conversation, thus tricking the user into believing that they are being understood.

Weizenbaum chose the simulation of psychotherapeutic interviews because in this type of interaction, the therapist can adopt a stance of knowing very little of the real world, allowing ELIZA to function effectively without a deep knowledge of the context. For example, if a user says "I feel sad," ELIZA may respond with "Why do you feel sad?", a generic but appropriate response that maintains the illusion of meaningful conversation (Weizenbaum, 1966).

Definition and operation

Pattern matching chatbots use predefined rules to map questions and answers. For example, ELIZA, one of the first chatbots, used substitutions and templates of text patterns to simulate a therapeutic conversation, creating the illusion of understanding without really understanding the context of the interactions (Caldarini *et al.,* 2022). These conversational assistants are effective at handling simple and predictable interactions, but lack the ability to adapt to more complex and dynamic contexts due to their reliance on strict, predefined rules.

The pattern matching methodology focuses on identifying specific patterns in user input to generate predefined responses. This approach may be sufficient in applications where interactions are repetitive and structured, such as in customer service or FAQ systems. However, the lack of ability to learn and adapt to new interactions significantly limits the effectiveness of these AI-based assistants in environments where greater contextual understanding and adaptability is required (Goldman, 2017).

Virtual assistants based on pattern matching represent a basic and economical solution for certain applications, but their usefulness is limited by their inability to handle the complexity and variability of the most advanced human interactions (Pradella, 2013).

Example of its implementation

ALICE (*artificial linguistics internet computer entity*) is another notable example that uses the *artificial intelligence markup language* (AIML) to define patterns and templates. This chatbot classifies user entries into categories and responds according to predefined templates that match input patterns (Xue, 2024).

AIML allows developers to create rule sets that determine how the chatbot should respond to different user entries. These rules are structured into templates that define specific text patterns and the corresponding responses.

Meanwhile, Liu and Lan (2016) state that when the user enters a query, ALICE searches its template database for a match and generates a response based on the corresponding template. This process allows ALICE to handle a wide variety of interactions quickly and efficiently, although it remains limited by the need for predefined templates and a lack of deep understanding of the context or user intent.

Using AIML in ALICE demonstrates how pattern matching-based virtual assistants can be customized and expanded by adding new templates and rules, allowing them to handle a wider range of interactions. However, like other rules-based conversational agents, ALICE cannot learn from new interactions or adapt to changes in context without manual intervention by developers (Ramírez and Valle, 2022).

Compared to conversational assistants based on natural language models, which can process and understand human language more flexibly and adaptively, virtual assistants such as ALICE offer a simpler and more economical solution for applications where interactions are predictable and repetitive (Hoyer *et al.*, 2020).

Methodology

This study adopted a systematic review methodology of scientific literature to analyze the characteristics and differences in the communicative efficiency of conversational assistants based on rules and natural language models. The search was carried out in recognized databases, including Google Scholar, Emerald, Elsevier, Taylor & Francis, IEEE/IEEE Xplore and FLACSO Andes, considering publications of the last five years and articles with public access (Perdomo, 2020).

The snowball technique was implemented to identify additional relevant studies in Google Scholar (Pucci *et al.,* 2020). Theoretical and explanatory foundations from previous methodologies were also included, considering those published before the analysis period, since they were relevant for studying conversational assistants based on rules and natural language.

The search strategy was structured in three main blocks of keywords, both in English and Spanish, related to the characteristics, differences and emerging trends in the study of conversational assistants based on rules and natural language. The references that matched these keywords in the title or body of the publications were selected and analyzed chronologically, forming a final sample of 175 relevant documents.

In addition, a content analysis of the selected literature was carried out to deepen the meaning of the terms, the differences and similarities, the distinctive characteristics and the emerging areas of research on conversational assistants structured in rules and those based on natural language models (Peralta and Guamán, 2020). This analysis allowed to identify conceptual definitions, typologies and applications of these systems, particularly in areas such as commerce and customer service.

Table 1

How pattern matching works in chatbots

Process	Description	Specific example
User input	The user enters a message to the *chatbot*.	"Hello, how are you?"
Input analysis	Identification of keywords in the message.	Hello and how you are identification
Predefined patterns	Database of patterns that the *chatbot* uses.	"Hello, how [verb]?"
Pattern matching	Comparison of the user's message with patterns.	Comparison with "Hello, how [verb]?"
Response selection	Selection of the corresponding response template.	"I'm fine, how are you?"
Response generation	Replacing markers in the response template.	Substitution of "[verb]" with "are"
Output to user	The *chatbot* sends the final response to the user.	"I'm fine, how are you?"

Note. This simplified schema shows how a rules-based chatbot uses pattern matching to process inputs and generate appropriate responses.

Advantages and limitations of rule-based chatbots

Chatbots operate according to a set of predefined rules, allowing them to provide consistent and predictable responses. They are ideal for tasks such as customer support, data collection and 24/7 support, offering significant benefits in terms of cost and simplicity of implementation. In addition, these virtual assistants are highly flexible in integrations with other data management or customer service systems, making them particularly useful in corporate and commercial environments (AirDroid, 2024).

By following strict and well-defined rules, rule-based virtual assistants can efficiently handle a high volume of interactions, reducing the workload of human agents and improving operational efficiency. However, their capacity is limited to the scenarios for which they were programmed. They cannot handle questions outside of their predefined rules and lack the ability to adapt to more complex or contextual interactions (Caldarini *et al.,* 2022).

The design and implementation of these automated dialog systems are relatively straightforward compared to virtual assistants based on natural language models. They do not require continuous learning or large volumes of data to function properly, making them a viable option for organizations with limited resources. In addition, its maintenance is less expensive and can be handled internally by IT teams without the need for artificial intelligence experts (Goldman, 2017).

On the other hand, rule-based virtual assistants have limited flexibility due to their inability to handle queries outside of predefined rules. They do not have the ability to learn and adapt to new situations, which restricts them to respond only within the parameters established initially. This means that any query that is not specifically scheduled within its rules cannot be effectively managed.

In addition, virtual assistants are suitable only for simple and straightforward tasks, as complex or multi-step interactions are often difficult to handle. This simplicity in their operation makes them useful for basic functions, but ineffective in scenarios that require greater sophistication in the processing of interactions (Xue *et al.,* 2024).

Another significant disadvantage is their inability to learn from experience. They cannot improve their responses over time and require manual updates to handle new queries, which increases the maintenance burden. As for the user experience, these chatbots are less effective at providing smooth conversational interaction and can be frustrating if queries do not exactly match the predefined rules. This can lead to an unsatisfactory user experience, especially when users expect more dynamic and adaptive responses (Hubtype, 2023; AirDroid, 2024; Xue *et al.,* 2024).

Chatbots in customer service areas

Rule-based chatbots are programs that follow a set of predefined instructions for interacting with users, particularly useful in customer service because of their ability to handle repetitive, structured queries efficiently.

These chatbots provide fast and consistent responses, often resulting in high customer satisfaction when queries are simple and straightforward (Nicolescu and Tudorache, 2022).

Nicolescu and Tudorache (2022) conducted a systematic review of the user experience with chatbots in customer service. They identified that the most influential factors in customer satisfaction include the relevance of responses and problem solving. Rule-based chatbots excel in these respects by providing fast and consistent responses, often resulting in high customer satisfaction when queries are *simple and straightforward.*

For its part, *Caldarini et al.* (2022) reviewed recent advances in chatbots, noting that although rule-based chatbots are limited in their ability to handle complex conversations, they remain valuable for specific, well-defined tasks in customer service. These systems are less expensive and easier to implement compared to chatbots based on language models, making them a viable option for many companies.

However, Ledro *et al.* (2022) highlighted in their study on Customer Relationship Management (CRM) that rules-based chatbots are effective in improving the customer experience at specific touchpoints. These chatbots can be integrated into CRM systems to provide fast and accurate answers to frequently asked questions, reducing the workload of customer service staff and improving operational efficiency.

In that sense, Ledro *et al.* (2022) explored the use of rules-based chatbots in the context of e-commerce. Their study showed that tools like Chatfuel allow companies to implement chatbots quickly and efficiently to improve customer interaction. The authors found that these chatbots are effective in managing frequent queries, improving customer satisfaction and optimizing the company's resources.

For its part, López *et al.* (2021) investigated the implementation of virtual assistants in CRM systems of technology companies. They found that rules-based chatbots, such as those implemented by the ManyChat platform, are crucial to providing ongoing support to customers. The research highlighted the importance of integrating these chatbots with other corporate systems to maximize their effectiveness and ensure consistent and rapid responses to customer queries.

Rule-based virtual assistants have been widely used in applications with simple and structured interactions, such as in customer service or FAQ systems (Shawar and Atwell, 2007). These chatbots stand out for their ability to provide fast and consistent responses in predictable scenarios, making them an effective solution for repetitive and well-defined tasks.

However, one of the main limitations of rules-based virtual assistants is their lack of adaptability and learning ability. These chatbots operate according to a predefined set of rules and cannot handle queries outside these parameters without manual updates (Xue *et al.,* 2024). This limitation restricts their use to specific and limited contexts, making them less suitable for situations that require dynamic and adaptive responses.

The psychological impact of ELIZA was significant, as it explored how computers could trick users into believing they were interacting with a human. This concept pioneered the field of artificial intelligence and laid the groundwork for future experiments, including the famous Turing Test proposed by Alan Turing in 1950. This test raises the question of whether a machine can exhibit intelligent behavior equivalent to or indistinguishable from that of a human being, which has been a central theme in research into artificial intelligence and the perception of human-machine interaction (Weizenbaum, 1966).

Natural language processing

Natural language processing (NLP) is a subdiscipline of artificial intelligence (AI) that focuses on understanding and generating human language, both spoken and written. In the context of marketing, the NLP is used to analyze large volumes of textual data, such as product reviews, interactions with voice assistants, and sales call transcripts. Traditional techniques include topic modeling and sentiment analysis, while more recent approaches rely on pre-trained language models and transfer learning for tasks such as automatic text generation and learning of multimodal representations (Hartmann and Netzer, 2023).

Another way of defining NLPs, along with text mining and natural language understanding, helps companies and organizations extract valuable information from unstructured data. As the business environment evolves, companies must integrate data from diverse sources to stay competitive. The NLP offers fast and efficient methods to process this data, facilitating tasks such as customer service automation and human resources management (Kwartler, 2021).

The development of natural language processing (NLP) has been crucial to the evolution of chatbots. The NLP allows chatbots to understand the context and meaning behind words, significantly improving human-computer interaction. Tools such as syntactic and semantic analysis, along with machine learning techniques, have allowed chatbots to interpret and respond more accurately to user queries (Caldarini *et al.,* 2022).

Since their introduction, transformers have been the basis of many advanced models, such as BERT (*Bidirectional Encoder Representations from Transformers*) and the GPT (*Generative Pre-trained Transformer series*). BERT, developed by Devlin (2019), was a significant advance as it allowed for bidirectional comprehension of the text, improving accuracy in several NL tasks (Laranjo *et al.*, 2018).

New scenario for using ChatGPT

Natural Language Processing (NLP) has advanced significantly thanks to natural language models, which have revolutionized the way machines understand and generate text. One of the most important milestones in this field was the introduction of transformer models in 2017, through the article "Attention is all you need" by Vaswani *et al.* (2017) These models have overcome the limitations of recurrent neural networks (RNNs) by using attention mechanisms to manage long-term relationships in text sequences.

Transformers have been the basis of advanced models such as BERT (*Bidirectional Encoder Representations from Transformers*), developed by Devlin *et al*. (2019) BERT enabled two-way understanding of the text, improving accuracy in various NLP tasks. Another prominent example is the GPT (*Generative Pre-trained Transformer*) series of OpenAI, which includes models such as GPT-1, GPT-2, GPT-3 and the recently released GPT-4. These models have shown a continuous increase in the number of parameters and capabilities. For example, GPT-3, with 175 billion parameters, has demonstrated advanced skills in text generation and language comprehension.

The even larger, multimodal GPT-4 incorporates 1.8 trillion parameters, allowing it to handle a wider variety of tasks with greater accuracy and efficiency. These models have been critical for applications across multiple domains, transforming the way people interact with technology and handle information.

In that sense, natural language models have been essential for applications in various fields, such as education, medicine and customer service, transforming interaction with technology. The benefits of these models include significant improvements in language comprehension, more accurate and efficient text generation, and advanced capabilities in a variety of natural language processing-related tasks. For the authors of this study, the present and future of communication between humans and machines is natural language.

Chatbots based on natural language

Natural language virtual assistants are computer programs that allow interacting with users through conversational interfaces. They use natural language comprehension platforms, such as Dialogflow and IBM Watson Assistant, to develop conversational agents that can be integrated into mobile applications, websites, and interactive voice response systems (Bhattacharyya, 2024).

On the other hand, Huang and Gursoy (2024) mention that virtual assistants using natural language models are systems designed to improve customer satisfaction during online interactions. They use different language styles (abstract or concrete) depending on the stage of the customer's decision-making process, providing emotional and informative support effectively. These virtual assistants are able to tailor their communication to deliver a more personalized and relevant experience.

For Ciechanowski *et al.* (2019), a chatbot is a conversation platform that communicates with the user through natural language, using applications, software or computer interfaces. These chatbots are based on technical applications of artificial intelligence that allow a fluent and natural interaction between humans and machines. The artificial intelligence applied in these chatbots facilitates the management of business processes, improving efficiency and customization of customer service.

For Bhattacharyya (2024) chatbots powered by large language models (LLMs) are artificial intelligence tools designed to interact with users through the use of natural language processing (NLP). These chatbots can understand and generate text in a consistent way, responding to customer queries in real time. They use advanced NLP techniques and are trained on large amounts of data to improve their accuracy and relevance in responses.

These conversational assistants have proven to be highly efficient in business process management, enabling customer service automation, cost reduction, and improved customer satisfaction through 24/7 availability and customization of responses (Ciechanowski, 2019).

AI-based wizards can be developed using agile methodologies that enable continuous system adaptation and improvement. Usability assessment is critical to ensure that chatbots meet the requirements of accuracy, functionality, and user satisfaction (Paschek *et al.,* 2017).

Communication efficiency between both types of virtual assistants

The communication efficiency of rules-based virtual assistants and natural language (NLP) models has been the subject of several studies, highlighting key differences in their performance and applicability. Rule-based chatbots operate by applying predefined conversation flows and rely heavily on specific keywords. This allows them to execute simple and repetitive tasks with high efficiency, but their ability to adapt to more complex queries is limited.

According to Buhalis and Yen (2020), these chatbots can be frustrating for users when they fail to handle natural language variations, which frequently leads to errors and misunderstandings. In contrast, NLP-based chatbots use advanced machine learning algorithms to interpret and generate natural language responses. These chatbots are able to understand the context and intention of the user, offering more precise and personalized answers.

Amalia and Suprayogi (2019) highlight that although the development and implementation of NLP-based chatbots require greater investment in terms of data and processing, their ability to learn and improve over time makes them a more efficient tool for handling complex and diverse interactions.

A comparative study by Hu *et al.* (2018) in the tourism sector showed that NLP-based chatbots outperform rules-based chatbots in terms of customer satisfaction and query resolution. NLP-based chatbots not only understand what the user is saying, but also the tone and context of the conversation, allowing them to deliver a more seamless and effective user experience. This ability to adapt and customize results in greater efficiency and effectiveness in communication, especially in environments where user queries are varied and complex.

Studies in the business field, such as Jindal *et al.* (2020), have shown that the implementation of NLP-based chatbots can lead to a significant improvement in operational efficiency and customer satisfaction. These virtual assistants can handle a higher query load simultaneously and provide more accurate responses, reducing the need for human intervention. Despite initial challenges in their development, the long-term benefits of NLP-based conversational assistants in terms of scalability and adaptability greatly outweigh rules-based chatbots, making them a preferred choice for many organizations (Ling *et al.*, 2021).

Table 2
Systematization of contributions to chatbots and natural language models

Authors	Year	Background	Relevant aspects
Weizenbaum	1966	Human-computer interaction	Psychological impact of ELIZA and the ability of computers to simulate human conversations.
Colby *et al.*	1971	Simulation of psychotherapy	Creation of PARRY, a *chatbot* that simulated a patient with schizophrenia, exploring the simulation of emotional states.
Winograd, T.	1972	Understanding natural language	Development of SHRDLU, a system that understood and generated natural language in the context of a world of blocks.
Schank and Abelson	1977	Theory of scripts and narrative structures	Development of theories on how artificial intelligence systems can understand and generate stories.
Bobrow and Winograd	1977	Dialog Models	Research in dialog models and understanding the structure of human conversations by *chatbots.*
Hayes-Roth and Hayes-Roth	1979	Interactive planning systems	Research on interactive planning systems and their application in *chatbots.*
Carbonell, J. G.	1980	Natural language learning and generation	Introduction of learning techniques to improve the generation and understanding of language in *chatbots.*
Wilensky, R.	1983	Language planning and understanding	Research in script-based planning for natural language understanding in *chatbots.*
Grosz and Sidner	1986	Dialog Structure	Studies on the structure and coherence of dialogs, essential for the development of interactive *chatbots.*
Allen, J. F.	1987	Temporary planning in dialogs	Research on how *chatbots* can understand and manage time planning in conversations.
Luger and Stubblefield	1998	Artificial Intelligence and Natural Language	Contributions to the field of AI and the application of NLP techniques in *chatbots*.

Authors	Year	Background	Relevant aspects
Abu Shawar and Atwell	2007	Simple and structured tasks	Effectiveness of rule-based *chatbots* in repetitive and predictable interactions.
Nicolescu and Tudorache	2022	Customer Service	Improving operational efficiency through rapid and consistent responses to frequent inquiries.
Caldarini *et al.*	2022	Efficiency in customer service	Effectiveness of rules-based *chatbots* in customer service.
Xue *et al.*	2024	Limitations and Maintenance	Limitations in the adaptability and manual maintenance of rules-based *chatbots.*
Vaswani *et al.*	2017	Natural language models	Introduction of transformers, overcoming the limitations of NRNs with attention mechanisms.
Devlin *et al.*	2019	Bi-directional models	Development of BERT, improving accuracy in various NLP tasks.
Hu *et al.*	2018	Learning and Adaptability	Machine learning algorithms for continuous improvement of *chatbot* responses.
Jindal *et al.*	2020	Handling complex queries	Advanced query handling capabilities not initially anticipated by NLP-based *chatbots.*
Hill *et al.*	2015	Human-computer interaction	Improvements in human-computer interaction using machine learning techniques.
Ding *et al.*	2024	Language Model Applications	Transformation of interaction and information management across multiple domains using GPT-4 and other advanced models.
Hartmann and Netzer	2023	PLN in marketing	Applications of the NLP for the analysis of textual data in marketing.
Badr	2024	Advances in natural language models	Increase in the number of parameters and capabilities of GPT models, improving text generation and comprehension.
El-Ateif *et al.*	2024	Applications across multiple domains	Applications of advanced NLP models in education, medicine and customer service.

Note. Key contributions from authors and development of chatbots and natural language processing from 1960 to 2024.

Current and future applications

For its part, Gnewuch *et al.* (2021) note the importance of assessing the effectiveness of virtual assistants not only in terms of technical accuracy, but also in terms of user experience and business outcomes. Continuous research and development in the design of virtual assistants focuses on improving these metrics to ensure that virtual assistants not only function properly, but also provide tangible value to users and organizations.

Currently, chatbots are used in a variety of fields, from customer service to education and health, however, virtual assistants can handle simple queries, and allow human agents to concentrate on more complex problems. In education, AI-managed virtual assistants can act as virtual tutors, providing personalized assistance to students (Chaves and Gerosa, 2021).

In the future, the integration of technologies such as conversational AI and language models is expected to continue to improve the effectiveness and versatility of chatbots, thus expanding their application in various industries and improving human-computer interaction (Wang and Jiang, 2020).

Results

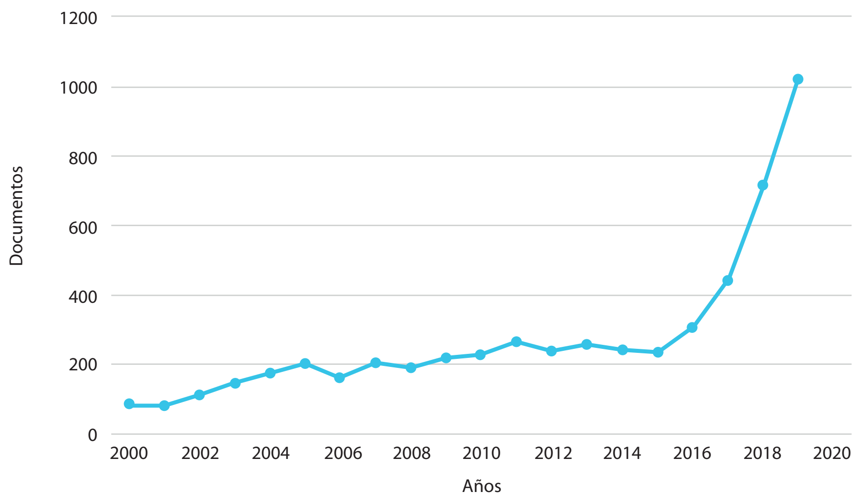
Rule-based chatbots are easier to build and maintain, and do not require continuous learning, which makes them more economical to implement, because they operate with predefined rules, provide consistent and predictable responses, which is beneficial for repetitive and well-defined tasks, such as in customer service (Hubtype, 2023). These virtual assistants can be rapidly deployed in applications where interactions are predictable and repetitive, improving operational efficiency without the need for complex configurations (Ledro *et al.,* 2022).

Conversational rules-based systems stand out for their ease of construction and maintenance, not relying on continuous learning, which makes them inexpensive and accessible solutions. Operating under predefined rules, these systems provide consistent and predictable responses, being especially useful in repetitive and structured tasks, such as customer service (Laranjo *et al.*, 2018).

Inability to understand context and language variations can result in frustrating experiences for users, especially when queries do not match predefined rules. In addition, they require manual updates to handle new queries or changes in interaction patterns, which can increase the long-term maintenance burden (Xue, 2024).

Figure 1

Scopus search results on chatbot



Note. From Caldarini *et al*. (2022): Scopus search results, from 1970 to 2021, for keywords "chatbot" or "conversational agents" or "conversation system".

Discussion

The analysis of conversational assistants, both those structured in rules and those based on natural language models, reveals significant differences that impact their applicability and efficiency in specific contexts. These findings allow to establish scenarios in which each type of system is more suitable, highlighting not only its benefits, but also the challenges they present in its development and implementation.

Rules-based wizards are notable for their simplicity and speed of implementation, being effective tools for scenarios where interactions are predictable and structured, such as frequently asked questions (FAQ) systems or basic customer service. However, their inability to manage complex queries or adapt to new situations limits their application in dynamic environments. Conversely, systems based on natural language models offer more fluent and personalized communication, enabling adaptive interactions that understand the context and intentions of the user. This attribute makes them ideal for complex tasks, such as assisting in educational processes, medical services, or advanced e-commerce.

The efficiency of the conversational assistants depends largely on the type of task, the user profile and the context of use. For example, in sectors such as education, natural language-based systems allow learning to be personalized, adapting to the individual needs of each student. In the business environment, its ability to manage simultaneous and personalized interactions enhances the customer experience. However, their performance may be affected by technical limitations, such as the quality of training data, or by ethical issues related to user privacy.

Despite their advantages, assistants based on natural language models face significant challenges in their implementation. The need for large volumes of quality data, combined with the complexity of development processes, increases costs and implementation times. In addition, ethical management of the data used in training and transparency in the use of artificial intelligence are critical aspects that require attention. On the other hand, rules-based systems, although cheaper and faster to implement, have limited utility in contexts that require flexibility and deep understanding of language (Tuan-Jun *et al.*, 2024).

In that sense, the advance in natural language models, such as recent developments in transformer architectures and deep learning, suggests a promising future for conversational attendees. Integrating these technologies with other artificial intelligence systems, such as enhanced learning and computer vision, could significantly expand their capabilities, enabling applications in emerging areas such as mental health, augmented reality, and multimodal interaction. But these advances must be accompanied by clear regulations and strategies that ensure the balance between technological innovation and ethical accountability.

Conclusions

Rules-based wizards are notable for their simplicity and speed of implementation, being effective tools for scenarios where interactions are predictable and structured, such as frequently asked questions (FAQ) systems or basic customer service. However, their inability to manage complex queries or adapt to new situations limits their application in dynamic environments.

Conversely, systems based on natural language models offer more fluent and personalized communication, enabling adaptive interactions that understand the context and intentions of the user. This attribute makes them ideal for complex tasks, such as assisting in educational processes, medical services, or advanced e-commerce.

These capabilities not only enable more fluent and natural communication, but also improve the overall user experience by providing personalized and adaptive interactions. In addition, NLP-based virtual assistants have the ability to learn from past interactions and improve over time, a significant advantage over rule-based chatbots, which are limited to pre-programmed responses and cannot adapt to new situations or demands without manual intervention (Hu *et al.,* 2018). These attributes make NLP-based chatbots much more effective and versatile tools for addressing the dynamic challenges of customer service and other interactive applications.

The study demonstrated a clear superiority of chatbots based on natural language models (NLP) in terms of naturalness and adaptability. These assistants provide more fluid and contextual interactions, resulting in a significant improvement of the user experience. The ability of NLP-based chatbots to accurately understand and respond to a wide variety of queries, including those not initially anticipated, makes them especially valuable in dynamic and complex environments (Hoyer *et al.*, 2020).

Despite their limitations, rule-based virtual assistants continue to be useful in environments where predictability and structure are essential. Their simplicity, lower cost, and ease of deployment make them ideal for specific applications, such as FAQs and basic customer support. The consistency and speed of the implementation of these chatbots offer efficient solutions for repetitive and well-defined tasks.

Implementing wizards based on natural language models involves higher cost and complexity, which can be a significant challenge for organizations, but their ability to learn and adapt over time justifies long-term investment. The need for advanced infrastructure and large volumes of data to train these models is offset by the benefits in terms of user satisfaction and operational efficiency. Syntactic and semantic analysis, along with machine learning techniques, allows NLP-based chatbots to manage complex interactions effectively, improving the quality of communication between humans and machines.

In future research, it is critical to analyze how integrating these virtual assistants with other emerging technologies, such as artificial intelligence and deep learning, can further improve their performance and applicability. The continued evolution of natural language models, such as recent developments in transformer models, indicates a promising future for human-machine interaction, where communication becomes increasingly natural and effective.

References

Abu Shawar, B. and Atwell, E. (2007). *Chatbots: are they really useful?* LOAIT 2007 - International Workshop on Legal Ontologies and Artificial Intelligence Techniques, 29-40.

AirDroid. (2024). Rule-Based vs. AI Chatbot: Which One is Better? www.airdroid.com

Badr, Y. (2024). Evolution of large language models and their role in shaping general artificial intelligence. *Digital Transformation and Society, 3*(1), 1-2. https://doi.org/10.1108/DTS-02-2024-088

Bhattacharyya, S. S. (2024). Study of adoption of artificial intelligence technology-driven natural large language model-based chatbots by firms for customer service interaction. *Journal of Science and Technology Policy Management.* https://doi.org/10.1108/JSTPM-11-2023-0201

Buhalis, D. and Yen, C. L. (2020). Leveraging inter-tourists interactions via chatbots to bridge academia, tourism industries and future societies. *Information and Communication Technologies in Tourism*, 231-242. Springer.

Caldarini, G., Jaf, S. and McGarry, K. (2022). A Literature survey of recent advances in chatbots. *Information, 13*(1), 41. https://doi.org/10.3390/info13010041

Ciechanowski, L., Przegalinska, A., Magnuski, M. and Gloor, P. (2019). In the shades of the uncanny valley: An experimental study of human-chatbot interaction. *Future Generation Computer Systems, 92,* 539-548. https://doi.org/10.1016/j.future.2018.01.055

Chaves, A. P. and Gerosa, M. A. (2021). How Should My Chatbot Interact? A Survey on Human-Chatbot Interaction Design. *International Journal of Human-Computer Interaction, 37*(8), 729-758. https://doi.org/10.48550/arXiv.1904.02743

Dale, R. (2020). The return of the chatbots: The latest advances and challenges in chatbot technology. *Natural Language Engineering, 26*(6), 811-832. https://doi.org/10.1017/S1351324916000243

Devlin, J., Chang, M. W., Lee, K. and Toutanova, K. (2019). *BERT: Pre-training of deep bidirectional transformers for language understanding*. Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers), 4171-4186. https://doi.org/10.18653/v1/N19-1423.

Ding, R., He, W., Liu, J., Liu, T., Zhang, D. and Ni, S. (2021). Interpersonal Regulation Questionnaire (IRQ): Psychometric properties and gender differences in Chinese young adolescents. *Psychological assessment, 33*(4), e13-e28. https://doi.org/10.1037/pas0000997

El-Ateif, S., Idri, A. and Fernández-Alemán, J.L. (2024). On the differences between CNNs and vision transformers for COVID-19 diagnosis using CT and chest x-ray mono- and multimodality. *Data Technologies and Applications, ahead-of-print.* https://doi.org/10.1108/DTA-01-2023-0005

Goldman, E. (2017, september 29). Antes de Siri y Alexa, estaba ELIZA [Video]. andouTube. https://bit.ly/4g35ggK

Gnewuch, U., Morana, S. and Maedche, A. (2021). Designing conversational agents for services: reviewing design principles and evaluating their effectiveness. *Journal of the Association for Information Systems, 22*(1), 163-204. https://doi.org/10.1007/978-3-319-91800-6_2

Hartmann, J. and Netzer, O. (2023). Natural Language Processing in Marketing. En K. Sudhir y O. Toubia (eds.), *Artificial Intelligence in Marketing*, 20, 191-215). Emerald Publishing Limited.

Hill, J., Randolph Ford, W. and Farreras, I. G. (2015). Real conversations with artificial intelligence: a comparison between human–human online conversations and human–chatbot conversations. *Computers in Human Behavior, 49*, 245-250. https://doi.org/10.1016/j.chb.2015.02.026

Hoyer, W. D., Kroschke, M., Schmitt, B., Kraume, K. and Shankar, V. (2020). Transforming the customer experience through new technologies. *Journal of Service Research, 23*(1), 3-24. https://doi.org/10.1016/j.intmar.2020.04.001

Huang, Y. and Gursoy, D. (2024). Customers' online service encounter satisfaction with chatbots: interaction effects of language style and decision-making journey stage. *International Journal of Contemporary Hospitality Management*. https://doi.org/10.1108/IJCHM-11-2023-1800

Hubtype. (2023). Rule-Based Chatbots vs. AI Chatbots: Key Differences. www.hubtype.com

Kwartler, T. (2021). Text analytics and natural language processing. In M. Einhorn, M. Löffler, E. de Bellis, A. Herrmann y P. Burghartz (eds.), *The Machine Age of Customer Insight* (pp. 119-128). Emerald Publishing Limited.

Laranjo, L., Dunn, A. G., Tong, H. L. and Bashir, R. (2018). Conversational Agents in Healthcare: A Systematic Review. *Journal of the American Medical Informatics Association, 25*(9), 1248-1258.

Peralta Lara, D. C. and Guamán Gómez, V. J. (2020). Metodologías activas para la enseñanza y aprendizaje de los estudios sociales. *Sociedad & Tecnología, 3*(2), 2-10. https://doi.org/10.51247/st.v3i2.62

Ledro, C., Nosella, A. and Vinelli, A. (2022). Artificial intelligence in customer relationship management: literature review and future research directions. *Journal of Business & Industrial Marketing, 37*(13), 48-63. https://doi.org/10.1108/JBIM-07-2021-0332

Ling, C., Nasir, M. H. and Pitra, Z. (2021). Understanding customer experience with AI-driven chatbots: a dual-process theory perspective. *Journal of Business Research, 129,* 170-183.

Liu, B. and Lane, I. (2016). Attention-Based Recurrent Neural Network Models for Joint Intent Detection and Slot Filling. arXiv preprint arXiv:1609.01454.

López, N. V., González, N. A. and Rodríguez, C. C. (2021). Implementation of Chatbot in Online Commerce, and Open Innovation. *Journal of Open Innovation: Technology, Market, and Complexity, 7*(2), 125. https://doi.org/10.3390/joitmc7020125

Luo, X., Tong, S., Fang, Z. and Qu, Z. (2019). Frontiers: Machines vs. humans: The impact of artificial intelligence chatbot disclosure on customer purchases. *Marketing Science*, *38*(6), 937-947. https://doi.org/10.1287/mksc.2019.1192

Nicolescu, L. and Tudorache, M. T. (2022). Human-computer interaction in customer service: the experience with AI chatbots—a systematic literature review. *Electronics, 11*(10), 1579. https://doi.org/10.3390/electronics11101579

Paschek, D., Luminosu, C.T. and Draghici, A. (2017). Automating customer service through chatbots. *Procedia Computer Science, 121*, 350-358.

Pradella, C. (2013). Evaluating chatbot usability for improving business processes. *International Journal of Business Management, 8*(4), 45-60.

Pucci, V. R., Machado, R. A., Cardano, M., Kantorski, L. P. and Weiller, T. H. (2020). Técnica da entrevista discursiva em pesquisa qualitativa: relato de experiência. *Rev. enferm. UFSM*, e97-e97. https://doi.org/10.5902/2179769241680

Ramires Hernandez, P. and Valle Cruz, D. (2022). Los Asistentes virtuales basados en Inteligencia Artificial. *ReCIBE, Revista electrónica de Computación, Informática, Biomédica y Electrónica, 11*(2), C1-11. https://doi.org/10.32870/recibe.v11i2.251

Silverio, M. (2024, mayo 17). *ChatGPT: número de usuarios y estadísticas.* PrimeWeb. https://bit.ly/4eLMnOh

Tuan-Jun, G; Lee-Ying, Siew-Chin, Ch., Pey-Yun, Goh. A. (2024). Campus-based Chatbot System using Natural Language Processing and Neural Network. *Journal of Informatics and Web Engineering* https://doi.org/10.33093/jiwe.2024.3.1.7 © Universiti Telekom Sdn Bhd.

Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., Kaiser, L. and Polosukhin, I. (2017). Attention is All You Need. *Advances in Neural Information Processing Systems, 30.* https://bit.ly/4g3jZrT

Wang, X. and Jiang, Z. (2020). Recent advances in neural chatbots. *International Journal of Automation and Computing, 17*(2), 251-266.

Weizenbaum, J. (1966). ELIZA—a computer program for the study of natural language communication between man and machine. *Communications of the ACM, 9*(1), 36-45.

Xue, J., Wang, Y.-C., Wei, C., Liu, X., Woo, J. and Kuo, C.-C. J. (2024). Bias and fairness in chatbots: An overview. *APSIPA Transactions on Signal and Information Processing, 13*(2), e102. http://dx.doi.org/10.1561/116.00000064

Kumar, Y., Delgado, J., Kupershtein, E., Hannon, B., Gordon, Z., Li, J. J. and Morreale, P. (2023). *AssureAIDoctor- A Bias-Free AI Bot.* Department of Computer Science and Technology.Kean University Union NJ, USA. https://bit.ly/42HN4FS

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