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A FEASIBILITY STUDY OF AVAILABLE NATURAL LANGUAGE CHATBOT TECHNOLOGIES

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ABSTRACT

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This thesis investigates the feasibility of deploying natural language processing (NLP) chatbot artificial intelligence (AI) toolkits in industrial organisation to improve service and product quality as well as enhance product functionality. The study compares features, pricing models, deployment options, and other factors to identify suitable AI solutions for commercial deployment by conducting a review of the literature and market-available toolkits.

Evaluating the available NLP chatbot AI toolkits for commercial deployment supports organizations in identifying and implementing the most suitable solutions for their needs, leading to more efficient information management and improved human-computer interactions. Rasa emerged as the most suitable solution due to its robust data privacy provisions, extensive customization options, deployment flexibility, and active development.

Alternatively, a hybrid solution combining Rasa's framework with the advanced NLP capabilities of OpenAI API was suggested. This approach offers enhanced language understanding while maintaining data privacy and customizability, though cost and additional data privacy concerns related to the OpenAI API integration must be considered. The study contributes to the broader fields of AI integration, workflow optimization, and customer experience enhancement.

Keywords Chatbot, natural language processing, and artificial intelligence

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LIST OF ABBREVIATIONS

AI	Artificial Intelligence
API	Application Programming Interface
NLP	Natural Language Processing
NLU	Natural Language Understanding
UI	User Interface
CRM	Customer Relationship Management
NER	Named Entity Recognition

1. INTRODUCTION

In the year of 2023 increasingly digital world, artificial intelligence (AI) and natural language processing (NLP) technologies are rapidly transforming the way information is conveyed and consumed. Chatbots have emerged as a powerful and innovative medium for information delivery, evolving from their traditional role as customer engagement tools. This thesis focuses on the feasibility study of natural language chatbot technologies and their potential as information providers, empowering users with personalized, interactive, and accessible experiences.

As the demand for instant access to information grows, chatbots present an attractive solution, offering users the ability to obtain tailored and real-time data through conversational interfaces. This study aims to critically examine and evaluate various chatbot technologies, assessing their features, pricing, deployment models, development plans, deployment effort, usage statistics, and data source interfaces, to identify the most suitable solutions for diverse organisation needs and requirements.

Additionally, this thesis will address the importance of data privacy in the 2023 digital environment and explore the challenges and opportunities associated with implementing chatbot interfaces with NLP in various settings. By offering recommendations based on a comprehensive feasibility analysis, this study seeks to contribute to the broader understanding of chatbot technology as an information provider within the academic community and the industry at large.

The insights garnered from this feasibility study are expected to have significant implications for both businesses and individual users alike. By presenting a detailed and systematic assessment of available chatbot technologies, this thesis will serve as a valuable resource for organizations and individuals seeking to harness the potential of chatbot technology for information dissemination. Furthermore, the practical recommendations and insights provided aim to empower users to make well-informed decisions when implementing chatbot solutions, allowing them to reap the benefits of this revolutionary technology.

1.1. Fields of the Study

This study intersects the domains of Artificial Intelligence (AI), Computer Science, Information Technology (IT), and Business Management. The rapid progress in AI, particularly in Natural Language Processing (NLP), has led to the growth of chatbot technologies, a subject that is closely tied to computer science. This thesis researches the multi-layered nature of chatbot technologies, looking at their design, how they are implemented, and how they are used in real-world settings. In addition, it explores aspects of IT by studying different deployment plans, development strategies, and integration of chatbot solutions. From a business management perspective, the research evaluates the cost-efficiency and strategic benefits of using chatbot technologies within organizations. The interplay of these four fields - AI, Computer Science, IT, and Business Management - provides the foundation for this thesis, which aims to give a comprehensive feasibility study of natural language chatbot technologies for information provision.

1.2. Research Question

What is the most suitable chatbot platform for organization considering factors such as data privacy, training on manuals, integration with existing systems, cost-effectiveness, and deployment challenges?

1.3. Limitations of the Study

Despite the comprehensive nature of this study, it is not without its limitations, which can be viewed in the context of constraints on time, resources, and the scope of research.

- Lack of practical testing: One of the major limitations of this study was the inability to perform practical testing of the various NLP chatbot solutions identified. Although the study provided a systematic methodology for assessing and selecting chatbot solutions based on theoretical evaluation criteria, the lack of practical, hands-on testing could limit the depth of understanding and evaluation. Real-world testing could provide insights into the usability, robustness, and performance of these solutions in a working environment, which might differ from theoretical expectations.

- Time constraints: The research was conducted within a limited timeframe, which may have restricted the amount of data that could be collected and analysed. This could potentially limit the comprehensiveness of the market analysis, and the number of chatbot solutions that were evaluated.

- Dynamic nature of AI technologies: The field of AI and NLP is rapidly evolving, with new advancements and updates to existing technologies happening frequently. Given this, the research findings might face limitations in terms of their future applicability, as newer, more advanced chatbot solutions may enter the market post the cut-off date of this study.

- Reliance on published information: The study heavily relied on published literature, articles, and product documentation for gathering information about various chatbot solutions. This might lead to biases or inaccuracies if these sources are outdated, biased, or contain errors.

The limitations outlined above should be considered when interpreting the findings of this study. Future research could address these limitations by incorporating practical testing, extending the timeframe of the study, including more chatbot solutions in the evaluation, and gathering primary data.

1.4 Summary of the Study

Literature Review: The study began with a thorough review of the literature surrounding NLP chatbot technologies, exploring their benefits, limitations, and use cases in organizational contexts. The review highlighted the importance of data privacy in chatbot deployment and discussed various deployment models along with their pros and cons. The OpenAI API's potential for creating custom NLP models was also evaluated.

Methodology: The study adopted a systematic approach to identify and evaluate potential NLP chatbot solutions. This involved a literature review, market analysis, and a comprehensive evaluation based on several criteria such as data privacy, training features, pricing models, and deployment efforts. The goal was to determine the most suitable chatbot solution.

Results: The results section compared different NLP chatbot solutions identified in the study, outlining the strengths and weaknesses of each solution. The findings were based on the defined criteria, providing insights into how well these chatbot solutions could meet organizational requirements.

Discussion: The discussion detailed the unique strengths and limitations of various chatbot platforms, underlining the importance of data privacy. It also addressed ethical considerations in deploying chatbots and identified key changes in human interaction due to chatbot deployment. The importance of addressing broader societal implications and ethical concerns was emphasized.

Conclusion: The conclusion encapsulated a comparative analysis of NLP chatbot solutions, suggesting Rasa as the most suitable solution for companies prioritizing data privacy and utilizing manuals for chatbot training. An alternative solution, a hybrid approach using Rasa and OpenAI API, was also proposed. The study concluded with recommendations for future research on emerging chatbot technologies and their long-term impacts.

The thesis discusses the feasibility of natural language chatbot technologies, guided by my fascination with the transformative power of AI and my academic background as well as the case company’s interest in the current state of the field and possible benefits of chatbot implementation. Through the exploration of various chatbot solutions and their potential to reshape the way information is processed, this study aspires to contribute to the field and pave the way for a more engaging, personalized, and accessible information landscape.

2. LITERATURE REVIEW

2.1. An Overview of Chatbot Technologies

Chatbot technologies have been playing a major role in the customer service revolution over the past decade, enabling businesses to automate and optimize interactions with their users. To better understand these transformative technologies, it is important to investigate their history and evolution, as well as explore their diverse use cases. In doing so, this literature review will provide an overview of the different types of chatbots, the machine learning algorithms that power them, their architecture, and their key components.

2.1.1. Evolution and History of Chatbots

The concept of chatbot technology dates to the 1960s, with the development of the first-ever chatbot, ELIZA, by Joseph Weisenbaum at MIT. ELIZA used simple pattern matching and substitution techniques to simulate conversation, primarily mimicking a Rogerian psychotherapist (Weisenbaum, 1966). Though ELIZA's functionality was limited compared to modern chatbots, for example, it did not learn from past conversations and did not have capacities to have long ones, it laid the foundation for the development of future chatbot systems.

Subsequently, the 1970s and 1980s saw the emergence of more sophisticated chatbots, such as PARRY by Kenneth Colby, which attempted to model the behaviour of a paranoid schizophrenic (Colby, 1975). In the early 1990s, the creation of the first general-purpose chatbot, Jabberwacky, by Rollo Carpenter, marked another milestone in chatbot history. Jabberwacky was designed to learn from its interactions with users, thereby refining its responses and emulating human-like conversation (Carpenter, 2005).

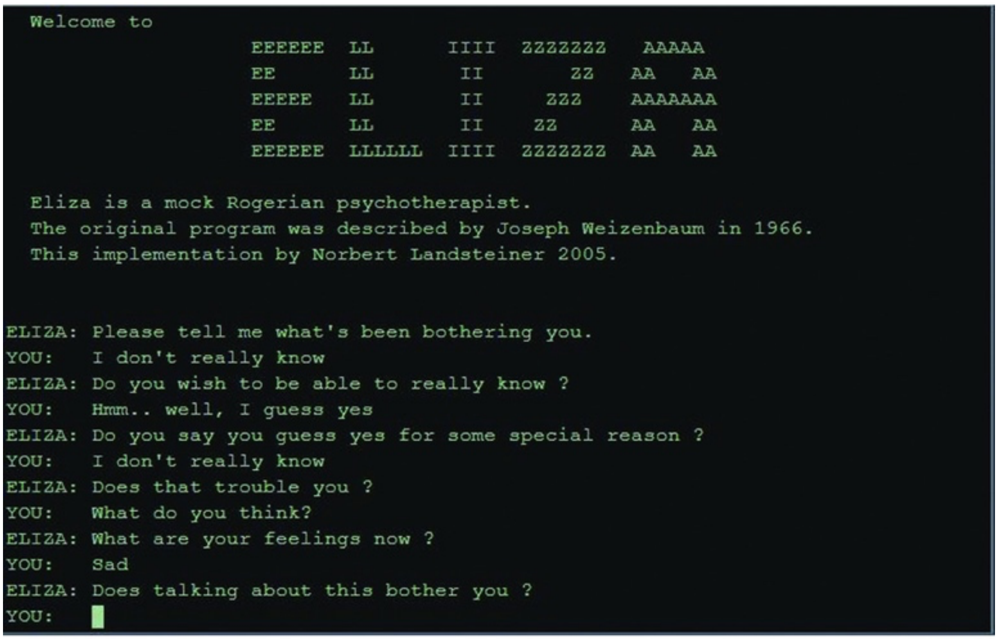

Figure 1. ELIZA chatbot mimicking Rogerian Psychotherapist

In the early 2000s, the advent of commercial chatbots such as SmarterChild and the development of the ALICE (Artificial Linguistic Internet Computer Entity) chatbot marked the beginning of chatbots as they are known closer to 2023 (Wallace, 2003). With the emergence of smartphones and messaging applications, chatbot technologies evolved further— as companies began integrating chatbots into platforms such as Facebook Messenger, WeChat, and Slack, they introduced a new era of customer service and user engagement.

The evolution of chatbots continued through the late 2000s and into the 2010s, becoming increasingly complex and capable. In 2010, Apple introduced Siri, a voice-activated virtual assistant integrated within its iOS devices. Siri demonstrated the possibilities of incorporating chatbot technology into everyday consumer electronics and marked a significant shift towards more natural language processing capabilities in chatbot technology.

This period also saw the emergence of IBM Watson, a powerful AI system that gained international fame after winning a game of Jeopardy! in 2011. Watson showcased the potential of AI and chatbot technology, not only for consumer interaction but also for tackling complex analytical problems.

In 2018, Google demonstrated Google Duplex's ability to mimic human speech patterns convincingly, showing a call between Google Assistant and a hair salon for appointment booking.

Finally, the progress of chatbot technology took a significant leap generative models appeared, a category of chatbots that can generate responses based on user input rather than pre-determined scripts. GPT (Generative Pretrained Transformer), developed by OpenAI, exemplifies this new wave of chatbot innovation.

GPT-1, introduced in 2018, was a transformer-based language model that utilized unsupervised learning to generate human-like text. Building on the success of GPT-1, GPT-2 was unveiled in 2019, which showed remarkable performance in several language tasks and demonstrated the ability to generate coherent and contextually relevant sentences over long passages of text. However, due to the model's ability to generate realistic, human-like text, OpenAI initially did not release the full version of GPT-2, citing concerns about potential misuse.

Despite these concerns, the potential of generative models was clear, leading to the development and release of GPT-3 in 2020. GPT-3 has 175 billion machine learning parameters and is capable of producing incredibly nuanced and contextually accurate text. It marked a significant milestone in the world of AI, with its capability to write essays, answer questions, translate languages, and even generate creative ideas. The model demonstrated the potential of AI to not only engage in complex conversations but also to create content that could potentially pass for human-authored text.

In addition to OpenAI's advancements, other players in the AI industry have developed generative models as well. For instance, Google's Meena and

Facebook's Blender bots have showcased similar capabilities in generating human-like text and carrying on engaging conversations.

As these technologies continue to improve, chatbots are expected to play an increasingly integral role in various aspects of life, from customer service and business operations to personal assistance and beyond. The journey of chatbot evolution, from the simple pattern matching of ELIZA to the sophisticated language generation of GPT-3 and beyond, is a testament to the incredible advancements in artificial intelligence and natural language processing.

2.1.2. Types of Chatbots and Machine Learning Algorithms

Chatbots can be broadly classified into four categories:

1. Rule-Based Chatbots: These chatbots follow predefined rules and decision trees to generate responses based on user inputs (Griol et al., 2014). They are relatively simple to implement and are primarily used for tasks with a limited scope, such as answering FAQs or guiding users through a specific process. However, they cannot handle complex or open-ended conversations.

2. AI-Based Chatbots: These chatbots leverage advanced NLP and machine learning (ML) techniques to understand and respond to user inputs (Shum et al., 2018). They can handle more nuanced conversations and improve their performance over time by learning from user interactions. AI-based chatbots can be further divided into two subcategories:

3. Retrieval-Based Chatbots: These chatbots use a predefined repository of responses to generate answers based on the similarity between user inputs and stored phrases (Ameixa et al., 2014). They employ algorithms such as cosine similarity or word embeddings to identify the most appropriate response.

4. Generative Chatbots: These chatbots use sequence-to-sequence models and deep learning techniques, such as recurrent neural networks (RNNs) and transformers, to generate responses by predicting the next word or phrase in a sentence (Sutskever et al., 2014; Vaswani et al., 2017). Generative chatbots have the potential to provide more dynamic and context-aware responses compared to retrieval-based chatbots, but may also produce unpredictable or inappropriate answers due to the complexities associated with language generation.

2.1.3. Chatbot Architecture and Key Components

The architecture of a chatbot typically consists of several key components, which work together to process user inputs and generate relevant responses (Shawar & Atwell, 2007).

User Interface (UI): The UI serves as the platform through which users interact with the chatbot, whether via text or voice. Chatbots can be integrated into various platforms, such as messaging applications, websites, or voice assistants.

Natural Language Processing (NLP): The NLP component is responsible for understanding and interpreting user inputs. It encompasses a range of tasks, including tokenisation, part-of-speech tagging, named entity recognition, and sentiment analysis (Manning et al., 2014).

Dialogue Management: This component manages the flow of conversation by keeping track of the conversation context and user intents. It uses this information to determine the most appropriate response or action to take based on the chatbot's capabilities (Serban et al., 2016).

Response Generation: This component is responsible for producing the chatbot's response based on the information provided by the NLP and dialogue management components. In rule-based chatbots, responses are selected from a predefined set of answers, while AI-based chatbots may generate responses dynamically using machine learning algorithms.

Backend Integration: Chatbots often need to access external resources, such as databases or APIs, to provide relevant information or perform specific tasks. Backend integration enables chatbots to retrieve or update data from external systems as needed (Khairullah, 2018).

2.1.4. Chatbot Use Cases and Usage Statistics

Chatbots have been applied to a wide array of industries, demonstrating their versatility and potential to transform business operations. Some of the industries are:

Customer service: Chatbots have been widely adopted for customer service applications, handling tasks such as answering FAQs, resolving issues, and providing personalised support (Feine et al., 2019).

Sales and marketing: Chatbots can be used to guide customers through the sales funnel, recommend products or services based on user preferences, and even facilitate transactions (Kumar et al., 2017).

Human resources: Chatbots can assist with recruitment, onboarding, and employee engagement by providing information about job openings, company policies, and employee benefits (McTear et al., 2016).

Finance and banking: Chatbots can be used in the financial sector to provide account information, facilitate transactions, and offer financial advice (Zeng et al., 2018).

Healthcare: Chatbots can be utilised for health-related applications such as symptom checking, appointment scheduling, and medication reminders (Bickmore et al., 2010).

Chatbot technologies have come a long way since their inception, with advancements in AI and ML algorithms enabling the development of more sophisticated chatbots.

As chatbot technologies continue to evolve and mature, they are expected to generate annual cost savings of over $994 million by 2023, projecting 3 billion dollars by the end of the decade (Maryia F., 2021). Bank customer interactions are expected to be handled by over 90% by chatbots in the banking sector by 2022 (Dylan M., 2022). HR chatbots increased employee satisfaction by 43% and reduced HR response time by 70%. The Healthcare AI market is predicted to reach $6.6 billion by 2021 with a CAGR of 40% (Snigdha P., 2022). As chatbot technologies continue to evolve, they are expected to shape the future of customer service, user engagement, and business operations across diverse industries and chatbots already are widely adopted by smaller businesses (Nicola Bleu, 2023).

2.2. NLP Chatbots as a Tool for Dealing with Documented Information

The use of NLP chatbots can offer several advantages, such as enhancing efficiency, improving decision-making, and facilitating communication. However, there are also limitations and challenges associated with implementing these AI tools in industrial settings.

2.2.1. Advantages of Using NLP Chatbots in Industrial Organisations

- Improved efficiency: NLP chatbots can efficiently process and analyse large volumes of textual data, which is particularly valuable in industrial organisations where vast amounts of information are generated and documented daily (Liddy, 2001). By automating the process of sifting through data, chatbots can save valuable time and resources for employees and the organisation.

- Enhanced decision-making: NLP chatbots can help the organisation make better decisions by providing quick access to relevant information and data insights (Chen et al., 2018). By analysing documented information, chatbots can identify patterns and trends that can inform strategic decision-making and improve overall organisational performance.

- Facilitated communication: Chatbots can facilitate communication within industrial organisations by providing a convenient and user-friendly interface for accessing documented information (Nadeau & Sekine, 2007). Employees can interact with chatbots using natural language, making it easier for them to obtain the information they need to complete tasks or make decisions.

- Personalised assistance: NLP chatbots can provide personalised assistance by understanding users' individual preferences, contexts, and requirements (Radziwill & Benton, 2017; Giridhar, 2023). By adapting to the unique needs of each user, chatbots can deliver tailored support, resulting in improved user experiences and increased satisfaction.

2.2.2. Limitations and Challenges of Implementing NLP Chatbots

- Limited understanding of complex language structures: While NLP chatbots have made significant progress in understanding and processing natural language, they still struggle with complex language structures and idiomatic expressions (Hirschberg & Manning, 2015). This limitation may result in chatbots misunderstanding user inputs or generating inappropriate or irrelevant responses.

- Inaccurate information: In some cases, NLP chatbots may retrieve or present inaccurate information, leading to potential negative consequences for decision-making or user satisfaction (Wang & Lemon, 2013). Ensuring the accuracy of chatbot responses is crucial for maintaining user trust and reliability.

- Data confidentiality and privacy: When implementing NLP chatbots in industrial organisations, data confidentiality and privacy must be considered (Moro & Rita, 2017). This involves ensuring that chatbots only access the necessary information and that they comply with data protection regulations.

- Integration challenges: Integrating NLP chatbots with existing systems, databases, and data sources within industrial organisations can be challenging (Liddy, 2001). Ensuring seamless integration may require significant effort and resources.

NLP chatbots offer a valuable AI toolkit for handling documented information in industrial organisations, providing various advantages such as improved efficiency, enhanced decision-making, and facilitate communication. However, there are also limitations and challenges associated with implementing these AI tools, including issues with complex language understanding, inaccurate information, data confidentiality, and integration challenges. As chatbot technology continues to evolve, addressing these limitations and challenges will be critical to realizing the full potential of NLP chatbots in industrial settings.

2.3. Key Features of NLP Chatbot Toolkits Relevant to an Organisation

NLP chatbot toolkits come with various features that are beneficial for an organisation in different ways. These features play a crucial role in enabling chatbots to process, understand, and respond to natural language inputs effectively while ensuring that the training on documented information and data confidentiality is maintained.

2.3.1. Natural Language Understanding

Natural Language Understanding (NLU) is one of the core components of NLP chatbot toolkits, responsible for interpreting and extracting meaning from user inputs (Mikolov et al., 2013). NLU enables chatbots to understand user queries, identify their intent, and provide appropriate responses. It involves tasks such as tokenisation, part-of-speech tagging, parsing, and semantic role labelling, which help chatbots understand the structure and context of the input text. By incorporating NLU capabilities, organisation can ensure that their chatbots can effectively handle complex language inputs and deliver accurate responses.

2.3.2. Sentiment Analysis

Sentiment analysis is another essential feature of NLP chatbot toolkits, allowing chatbots to detect and analyse the emotional tone or sentiment expressed in user inputs (Pang & Lee, 2008). This feature enables chatbots to recognise positive, negative, or neutral emotions, as well as more specific emotions such as happiness, anger, or frustration. By understanding the sentiment of user inputs, chatbots can provide more empathetic and contextually relevant responses. For an organisation, sentiment analysis can be particularly useful in applications such as customer service, where understanding and addressing user emotions are crucial for enhancing user satisfaction and building trust.

2.3.3. Entity Recognition

Entity recognition, also known as Named Entity Recognition (NER), is a feature that enables chatbots to identify and classify specific entities such as names, dates, locations, and organisation within user inputs (Nadeau & Sekine, 2007). This feature is essential for chatbots to extract and process relevant information from user queries, allowing them to provide more accurate and context-specific responses. Entity recognition can be particularly valuable for the organisation that deals with large volumes of structured or unstructured data, as it enables chatbots to retrieve and present relevant information to users more effectively.

2.3.4. Data Privacy during Training

One of the critical concerns for organisations when implementing chatbots is ensuring that the training data and documented information are protected from unauthorised access or leaks. NLP chatbot toolkits should offer data privacy features that enable organisations to train chatbots using their data while ensuring that the information remains confidential. This includes techniques such as data encryption, access controls, and data anonymisation. By incorporating these features, organisations can maintain data confidentiality while improving the chatbot's accuracy and effectiveness through training on their specific data.

2.3.5. Additional Important Factors

NLP chatbot toolkits come with various features that are relevant for organisations, not only the key features discussed earlier but also other important factors that can impact the effectiveness of a chatbot deployment, such as the ease of integration with existing organisational systems and infrastructure, scalability, and adaptability to diverse use cases.

When selecting an NLP chatbot toolkit, organisations must consider the ease with which the chatbot can be integrated into their existing systems and infrastructure. Chatbots should be compatible with the organisation's current technology stack, communication channels, and workflows. This may include integration with Customer Relationship Management (CRM) systems, help desk platforms, messaging applications, and social media platforms. Seamless integration with existing systems can help organisations unlock the full potential of chatbots by allowing them to communicate effectively with users and other systems, streamline processes, and reduce response times.

Scalability is another crucial factor to consider when selecting an NLP chatbot toolkit. As the organisation grows and the volume of user interactions increases, the chatbot should be able to handle the increased workload without compromising performance. Scalable chatbot toolkits can adapt to varying traffic loads, ensuring that the chatbot remains responsive and efficient even during peak times. Moreover, scalable chatbot solutions allow organisations to expand their chatbot functionality to cover additional use cases or languages without significant re-engineering or investment.

Organisations may have different use cases and requirements for chatbot deployment, and it is essential to select a toolkit that can accommodate these diverse needs. Some chatbot toolkits are specialised for specific industries or applications, while others offer more flexibility and customisation options. Organisations should look for chatbot toolkits that allow them to build, customise, and deploy chatbots for various purposes, including customer service, sales, marketing, and internal operations. A versatile chatbot toolkit can help organisations future-proof their investment and adapt to changing requirements over time.

2.4. Different Cost Structures of NLP Chatbot Toolkits

The cost models for NLP chatbot toolkits can vary significantly, as platforms differ in their pricing structures and the specific features offered. Some platforms charge a flat monthly or annual fee, while others employ usage-based or conversation-based pricing models.

OpenAI API and Dialogflow both provide usage-based pricing models. OpenAI API offers 1,000 free API calls per month, with subsequent calls charged at $0.00008 each, and has different models available. Dialogflow has a tiered pricing structure, with the first 1,000 text requests and 100 voice requests per month being free. The "Standard" tier charges $0.002 per text request and $0.0065 per voice request for up to 100,000 requests per month. These usage-based models are typically more affordable for small and medium-sized businesses.

IBM Watson Assistant uses a monthly subscription pricing model starting at $140 per month, including up to 1,000 monthly active users and $14 for every additional 100 users plus up to 10 000 API calls included. This model can be more cost-effective for businesses with high traffic or larger chatbot deployments but may be more expensive for those with low traffic.

Rasa offers a free community edition and a paid enterprise edition, with pricing based on the number of chatbot-handled conversations. The enterprise edition includes additional features such as data privacy and support.

Microsoft Bot Framework provides flexibility through its free "Standard" tier and a pay-as-you-go "Premium" tier for businesses with higher traffic and advanced requirements. The "Standard" tier allows for up to 10,000 messages per month when integrated with the Microsoft Language Understanding Intelligent Service (LUIS). The "Premium" tier charges $0.50 per 1,000 messages for the first 1 million messages, with the cost per 1,000 messages decreasing as the volume increases. This tier also includes additional features for example, faster response times and dedicated support.

Businesses should carefully evaluate the pricing models of different NLP chatbot toolkits to determine the best fit for their needs and budget. OpenAI API, Dialogflow, IBM Watson Assistant, Rasa, and Microsoft Bot Framework each offer unique pricing structures and features that cater to various business sizes and requirements.

2.5. Different Deployment Models of NLP Chatbot Toolkits

When implementing NLP chatbot toolkits in organisations, the choice of deployment model plays a critical role in determining the success of the integration with existing systems and infrastructure.

2.5.1. On-premises Deployment

In this model, the chatbot system is hosted entirely on an organisation's local servers and infrastructure. This approach provides a high level of data security and control over the environment, making it suitable for organisations with strict data privacy requirements (Arazy et al., 2010). However, on-premises deployment can be resource-intensive, requiring dedicated hardware, maintenance, and support. Additionally, it may not be as scalable or flexible as other deployment models, particularly for organisations that need to handle significant variations in chatbot usage. Examples of on-premises NLP chatbot platforms include Rasa (Rasa, 2023) and IBM Watson Assistant (IBM, 2023).

2.5.2. Cloud-based Deployment

Cloud-based deployment involves hosting the chatbot system on external servers provided by cloud service providers, such as Amazon Web Services (AWS), Microsoft Azure, or Google Cloud (Mell & Grance, 2011). This model offers advantages in terms of scalability, flexibility, and reduced upfront costs, as organisations can easily provision resources as needed. Cloud-based deployment is particularly suitable for fine-tuning and deploying large language models, as it provides access to powerful GPUs and TPUs for efficient training and inference. However, it can pose challenges related to data privacy, as data is stored on external servers, and costs associated with ongoing cloud service usage. Examples of cloud-based NLP chatbot platforms also include Dialogflow (Google Cloud, 2023) and Microsoft Bot Framework (Microsoft, 2023).

2.5.3. Hybrid Deployment

A hybrid deployment model combines elements of both on-premises and cloud-based deployments, using a mix of local infrastructure and cloud resources (Rimal et al., 2011). For instance, organisations can fine-tune a large language model on the cloud, taking advantage of the computational resources provided, and then deploy the fine-tuned model on local infrastructure for inference. This allows organisations to balance the benefits of both approaches, such as increased scalability and data control. However, managing the complexity of integrating and maintaining both cloud and on-premises resources can be a challenge.

The choice of a deployment model for NLP chatbot toolkits depends on factors such as an organisation's data privacy requirements, available resources, and priorities concerning scalability and cost. By carefully evaluating the advantages and limitations of each deployment model, organisations can determine the most suitable approach for integrating NLP chatbot toolkits with their existing systems and infrastructure.

2.6. Development Plans of NLP Chatbot Toolkits: Customisation, Scalability, and Open API Integration

The NLP chatbot toolkits are crucial for developing powerful and intelligent chatbots tailored to an organisation's diverse needs. The development plans of these toolkits determine their customisation and scalability potential, as well as their ability to integrate with other systems through open APIs.

Rasa is an open-source NLP chatbot framework that offers a highly customisable, scalable solution for organisations. It enables developers to build, train, and deploy chatbots using their data, algorithms, and domain-specific knowledge (Bocklisch et al., 2017). This customisation allows organisations to tailor chatbots to address unique use cases. Rasa's open-source nature facilitates continuous improvements and updates driven by an active community of developers. Additionally, Rasa supports open API integration, allowing developers to incorporate their code or integrate it with other systems as needed.

Dialogflow, a Google product, provides a range of customisation options and supports seamless integration with various platforms, APIs, and systems (Google Cloud, 2021). It enables developers to create custom intents and entities and design complex conversation flows using context and parameters. Dialogflow's flexibility lets organisations develop tailored chatbot solutions to meet specific requirements. Furthermore, Dialogflow's open API integration allows organisations to connect the chatbot with existing systems, offering a versatile solution.

IBM Watson Assistant offers high customisation and scalability for organisations (IBM, 2021). Developers can create custom intents, entities, and dialogue flows, building chatbots to meet an organisation's specific needs. Watson Assistant's cloud-based infrastructure enables easy scaling, ensuring the chatbot solution grows with the organisation. It also supports integration with various platforms, APIs, and services, including open API integration, facilitating seamless integration with existing organisational systems.

Microsoft Bot Framework provides extensive customisation and scalability options (Microsoft, 2021). Developers can build chatbots using Microsoft Language Understanding Intelligent Service (LUIS) and design custom conversation flows with Bot Framework Composer. This customisation enables organisations to create chatbots addressing unique use cases and requirements. The platform's integration with Azure services ensures scalability and flexibility, making it suitable for organisations of all sizes. Additionally, Microsoft Bot Framework supports open API integration, allowing for seamless connections with other systems and custom code.

The development plans of NLP chatbot toolkits, such as Rasa, Dialogflow, IBM Watson Assistant, and Microsoft Bot Framework, play a significant role in determining customisation, scalability, and open API integration potential. By selecting a toolkit that aligns with their needs and requirements, organisations can adopt a chatbot solution that is highly customisable, and scalable and integrates seamlessly with existing systems through open APIs.

2.6.1. Development Plan for Implementing a Custom NLP Model using OpenAI API and Training on Documented Data

Creating a custom NLP model using the OpenAI API allows organisations to fine-tune the model to specific domains or tasks using their documented data.

1. Preparing data: The first step is to collect and pre-process the organisation's documented data. This may involve cleaning and formatting text, as well as segmenting it into training, validation, and test sets.

2. Accessing the OpenAI API: Obtain an API key from OpenAI by creating an account and subscribing to a suitable plan on the OpenAI platform (OpenAI, n.d.).

3. Fine-tuning the model: Utilise the OpenAI API to fine-tune the base model on the prepared data. The fine-tuning process involves specifying the model architecture, training parameters, and providing the preprocessed training data.

4. Evaluation and validation: After fine-tuning, evaluate the model's performance on the validation set. This step is crucial for understanding the model's accuracy and effectiveness before deploying it.

5. Integration with existing systems: Integrate the custom NLP model into the organisation's existing systems, such as chatbot interfaces or other applications, using the OpenAI API for inference.

6. Monitoring and updating: Regularly monitor the model's performance and, if necessary, update it with new data or additional fine-tuning to maintain its effectiveness.

By following this development plan, organisations can leverage the OpenAI API to create custom NLP models tailored to their specific needs and train them on documented data. This process ensures the models can effectively understand and process the unique domain-specific language used by the organisation.

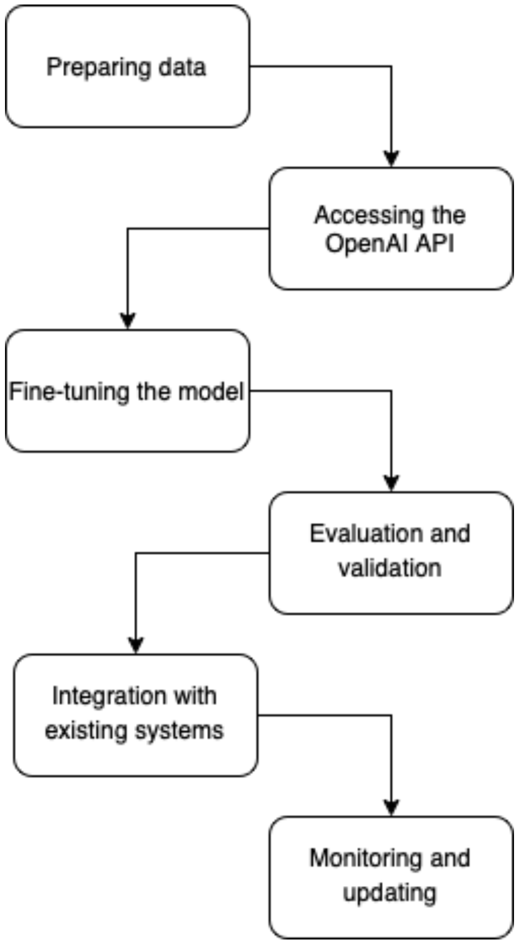

Figure 2. Development plan for implementing a custom model using OpenAI

2.7. Deployment Efforts for Implementing NLP Chatbot

The deployment efforts required for implementing NLP chatbot toolkits in organisations play a critical role in determining the adoption and success of these solutions.

Rasa's open-source nature requires organisations to allocate resources for development, maintenance, and support (Bocklisch et al., 2017). While it offers flexibility and control, the organisation must manage aspects such as server infrastructure and data storage. This could pose challenges in terms of resource allocation, especially for smaller organisations. However, Rasa's active community and extensive documentation make it a practically feasible solution for organisations with adequate technical expertise.

Dialogflow offers a user-friendly interface that simplifies deployment and maintenance (Google Cloud, 2021). As a cloud-based solution, it manages server infrastructure and data storage, reducing the need for dedicated resources. However, organisations might face challenges related to data privacy and control, as they have to trust Google's infrastructure with their data. Overall, Dialogflow's practical feasibility is high, especially for organisations seeking an easy-to-use, managed solution.

IBM Watson Assistant's cloud-based infrastructure simplifies deployment by handling server management and data storage (IBM, 2021). The platform offers a user-friendly interface and pre-built integrations that can reduce deployment efforts. However, organisations may face challenges related to data privacy and control, as data resides in IBM's cloud. The practical feasibility of IBM Watson Assistant is high for organisations looking for a robust, managed solution backed by a well-established vendor.

Microsoft Bot Framework integrates with Azure services, simplifying deployment and scaling (Microsoft, 2021). However, organisations must consider resource allocation for development and ongoing maintenance. Data privacy and control can be a challenge, as data is stored within Microsoft's cloud infrastructure. Nevertheless, Microsoft Bot Framework is a practically feasible option for organisations invested in Microsoft's ecosystem and seeking a comprehensive chatbot development platform.

The deployment efforts required for implementing NLP chatbot toolkits in organisations vary based on the platform and the organisation's needs. Rasa offers flexibility but may require more resources for deployment and maintenance. In contrast, Dialogflow, IBM Watson Assistant, and Microsoft Bot Framework are cloud-based solutions that simplify deployment but may pose challenges related to data privacy and control. Organisations must consider these factors when evaluating the practical feasibility of implementing NLP chatbot toolkits to ensure a successful deployment.

2.7.1 Deployment Efforts for Creating a Custom NLP Model Using the OpenAI API

Implementing a custom NLP model using the OpenAI API requires organisations to undertake several deployment efforts to ensure successful integration with existing systems and infrastructure.

Data management: Collecting, pre-processing, and managing the organisation's documented data can be time-consuming and may require dedicated resources, such as data engineers or data scientists, to handle these tasks effectively.

Technical expertise: Utilising the OpenAI API for fine-tuning the model requires knowledge of programming languages (for example, Python) and a clear understanding of NLP concepts, API usage, and best practices for model training.

Hardware and infrastructure: Although fine-tuning and inference using the OpenAI API take advantage of cloud-based resources, organisations may still need to consider their hardware and infrastructure requirements for tasks such as data preprocessing, integration with existing systems, and handling the increased network traffic generated by API calls.

API costs: Using the OpenAI API for fine-tuning and inference may entail costs associated with the subscription plan and the number of API calls made. Organisations should monitor these costs to ensure they stay within budget.

Model validation and evaluation: Organisations need to allocate time and resources for evaluating and validating the performance of the custom NLP model before deployment. This process may involve multiple iterations of fine-tuning and testing to achieve the desired level of accuracy and effectiveness.

Integration with existing systems: Integrating the custom NLP model with existing systems, such as chatbot interfaces or other applications, may require additional development efforts, as well as the collaboration of software developers, system administrators, and other stakeholders.

Ongoing maintenance and updates: Organisations must allocate resources for monitoring and maintaining the custom NLP model, ensuring its effectiveness and making updates as needed to address changes in documented data or evolving requirements.

Deploying a custom NLP model using the OpenAI API requires organisations to invest in data management, technical expertise, hardware and infrastructure, and ongoing maintenance. By understanding these deployment efforts and allocating appropriate resources, organisations can successfully implement a custom NLP model tailored to their specific needs, enhancing the efficiency and effectiveness of their chatbots and other applications.

2.8. Evaluating the Effectiveness and Potential of NLP Chatbot Toolkits in Improving Organisational Efficiency

The adoption of NLP chatbot toolkits, such as OpenAI API, BARD, and others, has been growing significantly in recent years, with organisations across various industries, including healthcare, finance, e-commerce, and customer service, increasingly integrating these tools into their systems (Grand View Research, 2020).

OpenAI API is a prominent NLP chatbot toolkit, offering a range of natural language processing capabilities, including sentiment analysis, entity recognition, and text generation (OpenAI, n.d.). Companies such as Microsoft, Adobe, and IBM have utilised OpenAI API for applications such as virtual assistants, customer service chatbots, and language translation services (Microsoft, n.d.; Adobe, n.d.; IBM, n.d.).

BARD (Business Automation through Robotic Design) is another NLP chatbot toolkit specifically designed for enterprise use cases, providing features such as natural language understanding, sentiment analysis, and intent recognition (BARD, n.d.). It has become a popular choice for companies seeking to implement chatbots for customer support, lead generation, and other business use cases.

A report by Grand View Research (2020) states that the global chatbot market size was valued at USD 2.6 billion in 2019, with an expected compound annual growth rate (CAGR) of 25.4% from 2020 to 2027. The report highlights the increasing demand for NLP chatbots across industries and their potential for improving organisational efficiency and reducing operational costs.

The growing usage statistics of NLP chatbot toolkits such as OpenAI API and BARD indicate their effectiveness in processing documented information and their potential for enhancing organisational efficiency. With the increasing demand for chatbots in various industries, their usage will likely continue to grow, leading to further advancements in NLP technology and the development of more sophisticated chatbot toolkits.

3. METHODOLOGY

This section outlines the methodology adopted for assessing and selecting suitable NLP chatbot solutions for organisational settings. The study aims to evaluate potential chatbot technology options based on criteria chosen by the company according to their main interests, such as data privacy, training features, pricing models, deployment models, development plans, deployment efforts, and usage statistics. The methodology comprises three primary stages:

1) identification of potential chatbot solutions

2) evaluation of the solutions

3) determining the most suitable solution

3.1. Identification of Potential Chatbot Solutions

An extensive review of the literature on chatbot technologies, natural language processing and AI was conducted to identify potential chatbot solutions suitable for organisational settings (Google Scholar, ResearchGate). This review was done by using different search engines, such as Google, and helped to establish a strong theoretical foundation and identify the current state of chatbot research and applications.

A market analysis was done as well to identify leading chatbot platforms, tools, and service providers (Freedman, 2023). The features, capabilities, pricing, and support provided by these solutions were examined to create a comprehensive comparison matrix.

3.2. Evaluation of the Solutions

Once potential chatbot solutions had been identified, a comprehensive evaluation was performed based on the following criteria:

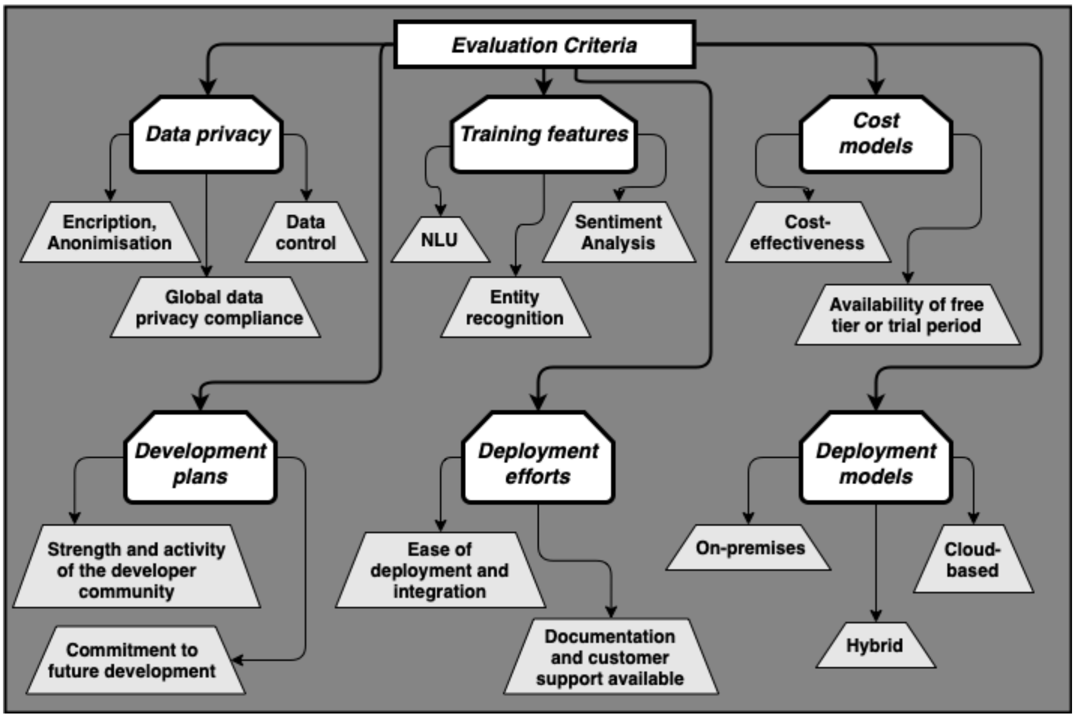

Figure 3. Evaluation criteria.

The data privacy and security measures employed by different chatbot providers were investigated. This includes examining their data storage practices, encryption methods, and compliance with relevant data protection regulations, considering the organisation's data protection requirements.

The chatbot toolkits' capabilities were evaluated for the availability of pre-trained models, fine-tuning options, and support for custom model creation.

The cost structure of each chatbot solution was found out, focusing on upfront costs, subscription fees, and additional charges for services such as API usage or storage.

The deployment options available were discussed, including on-premises, cloud-based, and hybrid models as well as the development plans of each chatbot solution, considering factors such as support for customisations, future enhancements, and integration with third-party systems.

An attempt was also made to evaluate deployment efforts for each of these chatbot solutions: ease of setup and configuration, platform compatibility, deployment options, scalability, customization and extensibility, cost and pricing.
To evaluate the simplicity of setting up and configuring various chatbot platforms, it is important to consider the learning curve, available documentation, and support resources for each solution (McTear et al., 2016).
In assessing the ease of integrating chatbot solutions with existing systems, communication channels, and platforms, it is crucial to examine compatibility, available integration options, and support for various channels (Gartner, 2020).

3.3. Determining the Most Suitable Solution

After evaluating the potential chatbot solutions based on the criteria mentioned above, the most suitable solution was determined. This selection was based on the solution's overall compliance with all factors and its ability to meet the organisation's specific needs and requirements.

By following this systematic approach, the study will help organisations make informed decisions when selecting an appropriate NLP chatbot solution, ensuring the successful integration and optimal performance of chatbot technology in their operations.

4. RESULTS

4.1. Overview of the Identified Chatbot Solutions

This section provides an overview of the identified chatbot solutions, including Dialogflow, Rasa, IBM Watson Assistant, Microsoft Bot Framework, and OpenAI API. A brief description of each chatbot solution, along with its key features and capabilities, is presented below.

4.1.1. Dialogflow

Dialogflow, developed by Google, is a natural language understanding (NLU) platform that allows developers to design and integrate conversational agents into various applications, including websites, mobile applications, messaging platforms, and IoT devices. It supports multiple languages and offers built-in machine learning capabilities that enable the chatbot to understand user inputs and respond accordingly. Dialogflow provides an intuitive visual interface for designing conversation flows and integrates seamlessly with other Google Cloud services.

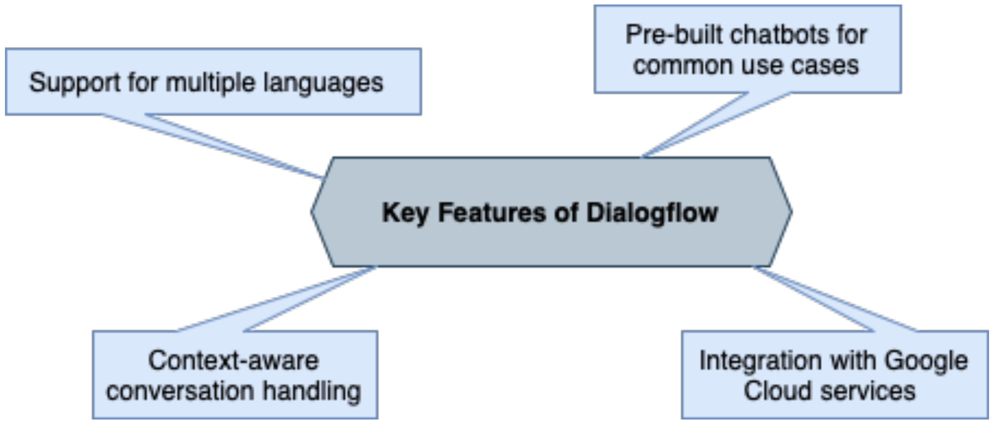

Figure 4. Fey features of Dialogflow

4.1.2. Rasa

Rasa is an open-source chatbot development platform that offers both NLU and dialogue management capabilities. It provides tools for developers to build custom chatbots, allowing for greater flexibility and control over the chatbot's behaviour. Rasa supports on-premises deployment, making it suitable for organisations with strict data privacy requirements. It can be integrated with various messaging platforms and offers a wide range of community-developed plugins and integrations.

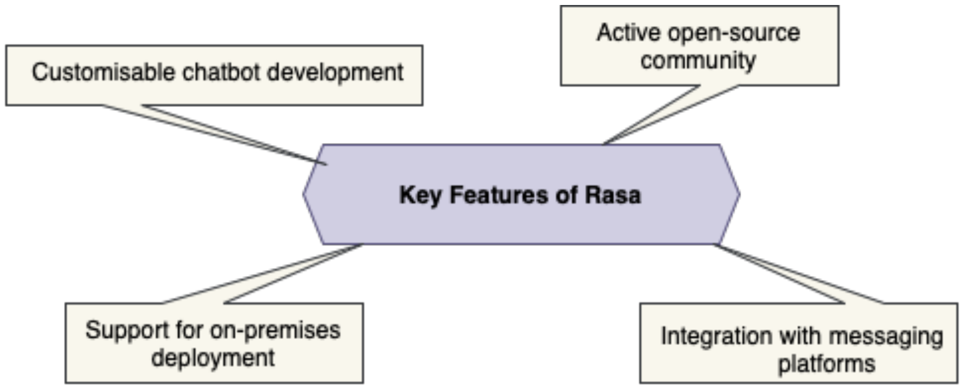

Figure 5. Rasa's key features

4.1.3. IBM Watson Assistant

IBM Watson Assistant is a conversational AI platform that enables developers to build, train, and deploy chatbots across multiple channels, including websites, mobile applications, and messaging platforms. It offers pre-built industry-specific content packs, along with the ability to train custom models using an organisation's data. Watson Assistant integrates with IBM Cloud services and other third-party platforms, allowing for a comprehensive and connected chatbot ecosystem.

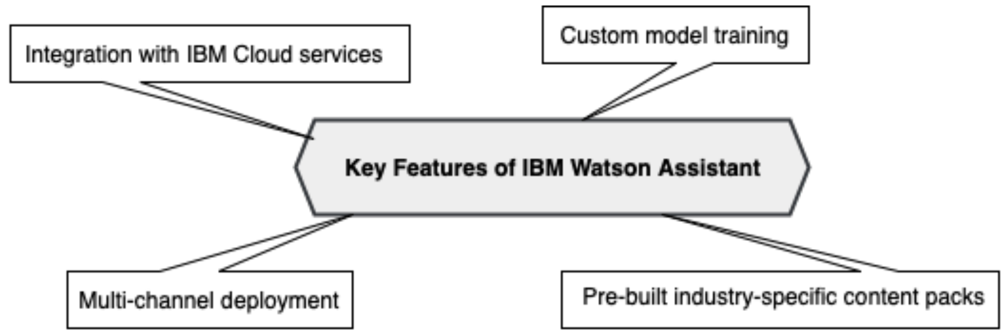

Figure 6. Key features of IBM Watson Assistant

4.1.4. Microsoft Bot Framework

Microsoft Bot Framework is a comprehensive platform for building, testing, and deploying chatbots across various channels, including websites, mobile applications, and messaging platforms. It supports both code-based and visual bot development, offering flexibility for developers with different levels of expertise. Microsoft Bot Framework is part of the larger Azure Bot Service, enabling seamless integration with other Azure services and third-party platforms.

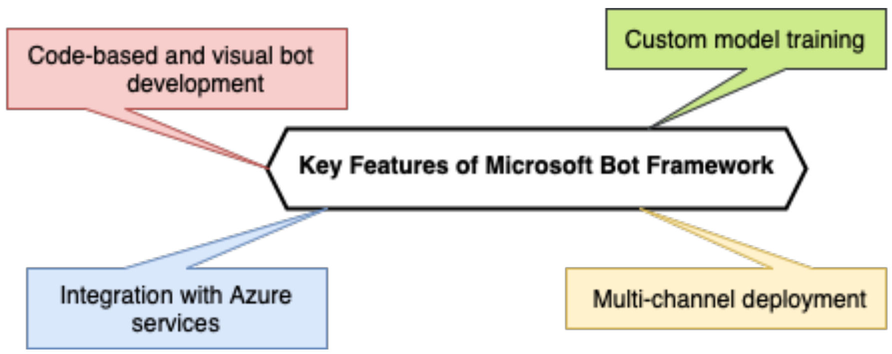

Figure 7. Microsoft Bot Framework's key features

4.1.5. OpenAI API

The OpenAI API provides access to the powerful GPT-3 language model, enabling developers to integrate advanced natural language processing capabilities into their chatbot solutions. The API supports various tasks, such as text generation, summarisation, translation, and question-answering. It allows developers to fine-tune the GPT-3 model on their data, ensuring that the chatbot is tailored to their specific domain or use case.

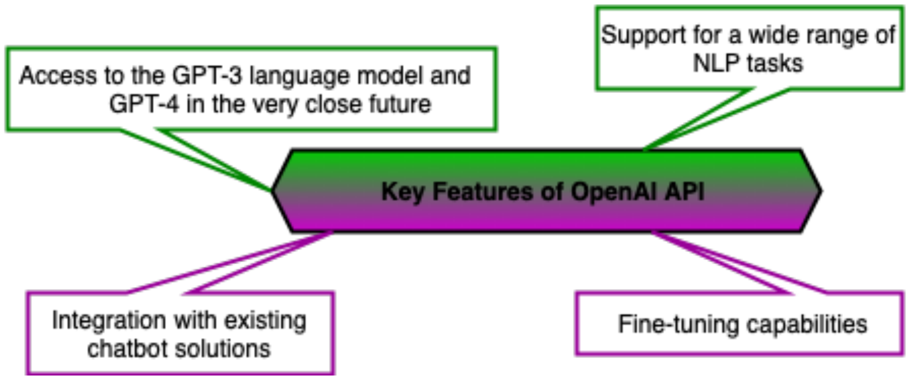

Figure 8. OpenAI API's key features

The identified chatbot solutions offer a range of features and capabilities to cater to different organisational requirements. Organisations can choose from these solutions based on their specific needs, such as data privacy, customisation, multi-channel deployment, and integration with existing systems and infrastructure.

4.2. Data Privacy and Security Provisions

Features/Platform	**Dialogflow**	**Rasa**	**IBM Watson Assistant**	**Microsoft Bot Framework**	**OpenAI API**
Compliance	GDPR, HIPAA, SOC 2	N/A (Self-hosted)	GDPR, HIPAA, CCPA, ISO	GDPR, HIPAA, ISO, FedRAMP	GDPR, CCPA
Data Encryption	In transit and at rest	Depends on deployment	In transit and at rest	In transit and at rest	In transit and at rest
Infrastructure	Google Cloud	Self-hosted (On-premises)	IBM Cloud	Azure	OpenAI Cloud Infrastructure
Authentication	Yes	Various methods	Yes	Yes	Yes
Access Control	Yes	Depends on deployment	Yes	Role-based	Depends on implementation
Audit Logs / Activity Monitoring	Yes	Depends on deployment	Yes	Yes	Depends on implementation
Open Source	No	Yes	No	SDK is open-source	No

Features/Platform	Dialogflow	Rasa	IBM Watson Assistant	Microsoft Bot Framework	OpenAI API
Data Privacy & Security Measures	Built-in	Adheres to best practices	Built-in	Built-in	Review policies and practices
Disaster Recovery & Redundancy	Google Cloud-based	Depends on deployment	IBM Cloud-based	Azure-based	Depends on implementation
Data Retention Policies	Configurable	Depends on deployment	Configurable	Configurable	Configurable
Data Sovereignty & Localization	Yes (Google Cloud Regions)	Depends on deployment	Yes (IBM Cloud Regions)	Yes (Azure Regions)	Limited (Review policies)
Third-Party Security Certifications	Yes	N/A (Self-hosted)	Yes	Yes	Yes

Table 1. The comparison table of candidates' data privacy features

Rasa, being an open-source platform, can be deployed on-premises, allowing organisations to have complete control over their data. Rasa supports various authentication methods and adheres to data protection best practices.

"Depends on deployment" means that the specific features, such as data encryption, access control, audit logs, or other data privacy and security measures, depend on how an organization chooses to deploy and configure the solution. In the case of Rasa, which is an open-source platform that can be self-hosted (on-premises), the implementation of these features is at the discretion of the organization deploying it. For example:

For example, if an organization deploys Rasa on its own servers or private cloud, it is up to the organization to ensure that data encryption is implemented for data in transit and at rest. They can choose to use their own encryption methods, tools, and policies.

Organizations can configure their Rasa deployment to incorporate their own access control measures, such as authentication, authorization, and role-based access. This depends on their specific requirements and security policies. Similarly, organizations can decide if they want to implement and maintain audit logs and activity monitoring as part of their Rasa deployment. They can use their own tools and solutions to monitor and log activities within the platform.

Dialogflow ensures data privacy and security by complying with various industry standards, including GDPR, HIPAA, and SOC 2. It offers encryption for data in transit and at rest and leverages Google Cloud's infrastructure for additional security measures.

IBM Watson Assistant complies with GDPR, HIPAA, and other data protection regulations. It provides encryption for data in transit and at rest and offers built-in measures for data privacy and security, such as access controls and audit logs.

Microsoft Bot Framework ensures data privacy and security by adhering to GDPR, HIPAA, and other regulations. It uses Azure's infrastructure to provide encryption for data in transit and at rest and includes features such as role-based access control and activity monitoring.

OpenAI API follows data retention policies and complies with GDPR. However, it is essential to carefully review the data handling policies and practices before integrating the API with a chatbot solution to ensure the required data privacy standards are met.

4.3. Training Features and Capabilities

Feature/Platform	**Dialogflow**	**Rasa**	**IBM Watson Assistant**	**Microsoft Bot Framework**	**OpenAI API**
Pre-built Agents	Yes (Common use cases)	No	Yes (Industry-specific)	No	No
Custom Training with User Data	Yes	Yes	Yes	Yes	Yes (Fine-tuning GPT-3)
Machine Learning Improvements	Continuous learning	Custom NLU models	Algorithms	Refining responses	Wide range of NLP tasks
Domain-specific Chatbot Tailoring	No	Yes (Custom NLU models)	Yes (Content packs)	No	Yes (Fine-tuning GPT-3)

Table 2. Comparison table of candidates' training features

Dialogflow provides pre-built agents for common use cases and supports training through user-provided data. It leverages machine learning to continuously improve the chatbot's understanding of user inputs.

Rasa offers customisable chatbot development with support for training on the organisation's data. It provides tools for creating custom NLU models and fine-tuning them based on specific use cases.

IBM Watson Assistant supports custom model training using the organisation's data and offers pre-built industry-specific content packs. It leverages machine learning algorithms to improve the chatbot's understanding and responses.

Microsoft Bot Framework supports training using user-provided data, customising the chatbot's understanding of user inputs. It uses machine learning to continuously refine the bot's responses based on user interactions.

OpenAI API enables fine-tuning the GPT-3 model on the organisation's data, ensuring that the chatbot is tailored to the specific domain or use case. It supports a wide range of NLP tasks, such as text generation, summarisation, translation, and question-answering.

4.4 Ways of Charging for Usage

Feature/Platform	**Dialogflow**	**Rasa**	**IBM Watson Assistant**	**Microsoft Bot Framework**	**OpenAI API**
Free Tier	Yes (Limited features)	Yes (Open-source)	Yes (Limited resources)	Yes (Limited resources)	N/A
Pay-as-you-go Plans	Yes (Based on usage)	N/A	No	Yes (Messages and storage)	Yes (Based on API usage)
Subscription Plans	No	Yes (Enterprise plans)	Yes (Users, messages, models)	No	Yes (Based on API usage)

Feature/Platform	Dialogflow	Rasa	IBM Watson Assistant	Microsoft Bot Framework	OpenAI API
Additional Support & Features	No	Yes (Enterprise plans)	Yes (Paid plans)	Yes (Paid plans)	Yes (Based on selected plan)
Custom Pricing Options	Yes	Yes	Yes	Yes	Yes

Table 3. Comparison table of candidates' pricing features

The five AI conversational platforms - Dialogflow, Rasa, IBM Watson Assistant, Microsoft Bot Framework, and OpenAI API - offer various pricing plans to accommodate different organizational needs and budget constraints.

All five platforms studied offer some form of free tier access. Dialogflow and IBM Watson Assistant provide limited features and resources, respectively, under their free tier. Rasa, an open-source platform, also offers free access to its services. Microsoft Bot Framework's free tier involves limited resources. On the other hand, the OpenAI API does not offer a free access tier.

With respect to payment plans, Dialogflow and the OpenAI API offer pay-as-you-go plans, with costs based on usage. Microsoft Bot Framework also has a similar pay-as-you-go model, where charges apply to messages and storage used. However, IBM Watson Assistant does not provide a pay-as-you-go option. Notably, Rasa does not have a specified pay-as-you-go model but does offer Enterprise plans under a subscription model.

Subscription plans are available in Rasa, IBM Watson Assistant, and the OpenAI API. For Rasa and IBM Watson, these plans include Enterprise and paid plans, respectively. Both of these platforms include costs for users, messages, and models. In contrast, the OpenAI API's subscription is based on API usage. Neither Dialogflow nor Microsoft Bot Framework currently offers subscription plans.

One significant factor in the choice of platform is the availability of additional support and features. These are not available with the free tier of Dialogflow, while

Rasa, IBM Watson Assistant, and Microsoft Bot Framework offer them under their Enterprise and paid plans. OpenAI API, on the other hand, provides additional features and support based on the selected plan.

Lastly, all five platforms offer custom pricing options, providing flexibility for organizations to negotiate and establish contracts based on their specific needs and usage patterns.

4.7.1. Costs of Each Solution

This section presents the cost models for the five AI conversational platforms based on an assumption of 1,000 active users and 1,000 text requests/messages per month, along with an additional 100 voice requests for Dialogflow for reference. For OpenAI API, an average text length of 10 tokens per request is assumed, which is approximately 10 words or characters, depending on the complexity and language of the text.

Dialogflow's cost model comprises two components: text and voice requests. For 1,000 text requests, the cost is $7 (1,000 * $0.007), and for 100 voice requests, it is $6 (100 * $0.06). Thus, the total estimated cost for Dialogflow is $13 per month.

Rasa, being an open-source platform, does not charge for usage. However, they do offer paid enterprise plans that provide additional support and features. The cost for these plans isn't specified and could vary depending on the specific needs of the organization.

For 1,000 active users and 1,000 messages per month, the Lite plan of IBM Watson Assistant would suffice, which is free. If additional features or user capacity are needed, the Plus plan is available, supporting more than 1,000 active users at a starting price of $140 per month.

For our base requirement of 1,000 messages per month, the free tier of Azure Bot Services, which includes Microsoft Bot Framework, would be sufficient. For organizations needing more capacity or additional features, costs would be determined by the resources consumed. The cost per 1,000 messages beyond the free tier was approximately $0.50.

OpenAI’s GPT-3 Turbo: 1,000 (messages) * 10 (tokens per message) / 1,000 (per 1K tokens) * $0.002 = $0.02

or

GPT-4: 1,000 (messages) * 10 (tokens per message) / 1,000 (per 1K tokens) * $0.03 = $0.3.

These calculations are for illustrative purposes and may not precisely reflect the actual cost for a specific use case. This model does not consider other potential costs, such as development, maintenance, and infrastructure. Hence, it is always advisable to consult directly with the platform provider since custom pricing options are available across all platforms to cater to specific organizational requirements.

4.5. Deployment Models

Feature/Platform	Dialogflow	Rasa	IBM Watson Assistant	Microsoft Bot Framework	OpenAI API
Cloud-based Deployment	Yes (Google Cloud)	Yes	Yes	Yes (Azure)	Yes
On-premises Deployment	No	Yes	Yes	No	No
Infrastructure Flexibility	Limited	High	High	Limited	Limited

Table 4. Comparison table of deployment models of candidates

Dialogflow supports cloud-based deployment, leveraging Google Cloud's infrastructure, whereas Rasa supports on-premises and cloud-based deployment, offering flexibility for organisations with different infrastructure requirements.

IBM Watson Assistant offers both cloud-based and on-premises deployment options, allowing organisations to choose the most suitable model for their infrastructure.

Microsoft Bot Framework is part of the Azure Bot Service, offering cloud-based deployment through Azure's infrastructure.

OpenAI API is a cloud-based solution, that requires organisations to access the API over the internet to utilise its NLP capabilities.

4.6. Development Plans

Feature/Platform	**Dialogflow**	**Rasa**	**IBM Watson Assistant**	**Microsoft Bot Framework**	**OpenAI API**
Improved Machine Learning	Yes	Yes	Yes	Yes	Yes (GPT-3 model)
Additional Language Support	Yes	Yes	Yes	Yes	Yes
Enhanced Platform Integrations	Yes (Google Cloud services)	Yes (With popular platforms)	Yes (IBM Cloud services)	Yes (With Azure services)	Yes
Expanded Community/Resources	Yes	Yes	Yes (Content packs)	Yes (Development experience)	Yes
Open-Source Platform	N/A	Yes	N/A	N/A	N/A

Table 5. Comparison table of development plans

Dialogflow's development plans include continuous improvements to its machine learning algorithms, support for additional languages, and enhanced integration with Google Cloud services.

Rasa, on the other hand, focuses on enhancing its open-source capabilities, improving its machine learning algorithms, and expanding its community support and resources.

IBM Watson Assistant plans to continuously refine its NLP algorithms, expand its pre-built content packs, and improve its integration with IBM Cloud services and other platforms.

Microsoft Bot Framework's development plans involve enhancing its NLP algorithms, adding new features and integrations, and improving the overall development experience for chatbot creators.

OpenAI API's development plans include refining its GPT-3 model, expanding support for fine-tuning on custom data and introducing new features and capabilities based on user feedback and requirements.

4.7. Deployment Efforts

Feature/Platform	Dialogflow	Rasa	IBM Watson Assistant	Microsoft Bot Framework	OpenAI API
Deployment Efforts	Low	Varies (depends on the model)	Straightforward (cloud & on-premises)	Low	Minimal (API integration)
Deployment Flexibility	Cloud-based	On-premises & cloud-based	Cloud-based & on-premises	Cloud-based (Azure)	Cloud-based (API)
Ease of Integration	Easy-to-use interface	Comprehensive documentation	Flexible options	Integration with Azure services	Requires API integration
Data Privacy Consideration	Standard compliance	Complete control over data	Standard compliance	Standard compliance	Must be reviewed and ensured

Table 6. Deployment efforts comparison

4.7.1. Ease of Setup and Getting Started

Dialogflow is known for its user-friendly interface and relatively low learning curve, with comprehensive documentation and community support available for users.

On the other hand, Rasa has a slightly steeper learning curve due to its open-source nature, but offers extensive documentation and a large community forum for support.

IBM Watson Assistant provides a straightforward setup and configuration process, accompanied by comprehensive documentation and support resources. The Microsoft Bot Framework is relatively simple to set up, as it is integrated with Azure services, which also provide extensive documentation and support. Lastly, the OpenAI API is easy to integrate for NLP capabilities, although it does require some programming knowledge and focuses primarily on API usage in its documentation.

4.7.2. Ease of Integration

Dialogflow offers a wide range of pre-built integrations and APIs and SDKs for custom integrations.

Rasa is highly flexible and supports both custom and popular messaging platform integrations.

Watson Assistant provides seamless integrations with various platforms and pre-built connectors, while also supporting integration with other IBM services.

The Microsoft Bot Framework can be integrated with popular messaging platforms and other Azure services through APIs and SDKs.

OpenAI API, focusing on NLP capabilities, requires organizations to handle other aspects of chatbot design and management, and integration depends on the organization's chatbot architecture and platforms used.

4.7.3. Scalability

Dialogflow, being cloud-based, automatically scales but might be limited by the Google Cloud infrastructure and pricing plans, while Rasa allows for customizable scaling but requires managing the underlying infrastructure.

IBM Watson Assistant scales automatically through the IBM Cloud infrastructure, but organizations must be aware of pricing plans and resource limits. Similarly, the Microsoft Bot Framework leverages the Azure cloud infrastructure for auto-scaling, requiring organizations to choose the right pricing plan for their scalability requirements.

The scalability of chatbots using the OpenAI API depends on the chatbot's architecture and underlying infrastructure, with organizations needing to consider pricing and rate limits imposed by OpenAI.

4.8. Selection of the Most Suitable Solution

NLP chatbot technology holds the potential to transform how organisations handle information. For a company that values data privacy and plans to use documented information such as manuals for chatbot training and considering the information provided in the previous sections, the analysis suggests that Rasa would be the most suitable solution for the given context.

Several factors contribute to this recommendation:

As the company prioritises securing the data, they train the chatbot on, Rasa's open-source framework enables them to have more control over their data. The company can choose between on-premises or cloud-based deployment, depending on their security requirements. Rasa also provides organisations with extensive customisation options, allowing them to build a chatbot tailored to their specific domain or use case. This feature is especially useful when working with specialised or industry-specific documented information, such as manuals.

Rasa's open-source nature makes it cost-effective compared to other solutions. While there are paid enterprise plans that include additional features and support services, the core functionalities can be utilised without any cost. Furthermore, Rasa's support for both on-premises and cloud-based deployment offers flexibility in choosing the best option for the company's infrastructure. This flexibility allows the organisation to align the chatbot solution with its existing systems and processes.

Rasa also has a strong focus on enhancing its open-source capabilities, improving machine learning algorithms, and expanding community support and resources. This commitment ensures that the company will benefit from continuous updates and improvements to the solution.

Based on the feasibility study, Rasa emerges as the most suitable NLP chatbot AI toolkit for the company considering data privacy, customisation options, cost-effectiveness, deployment flexibility, and active development. By implementing Rasa, the company can build a chatbot solution that meets their specific needs while effectively addressing data security concerns and leveraging documented information for example, manuals.

4.9. Alternative Solution

On the other hand, If the interest in utilising the OpenAI API is still there, a potential solution would be to create a custom chatbot using a combination of Rasa for the underlying framework and the OpenAI API for advanced NLP capabilities. This hybrid approach can provide the best of both worlds by combining the advantages of Rasa's customisation and data privacy options with the powerful language understanding capabilities of the OpenAI API.

Here's how this solution can be beneficial for the company:

By using Rasa as the base framework, the company can maintain control over their data and choose the deployment model that best suits its security requirements. Moreover, integrating the OpenAI API with the custom Rasa chatbot will allow the company to leverage GPT-3's advanced NLP capabilities. This integration can significantly enhance the chatbot's ability to understand complex user inputs, making it more effective when handling industry-specific documented information such as manuals.

Rasa's open-source framework allows the company to build a chatbot tailored to their specific domain or use case, while the integration with the OpenAI API adds a layer of enhanced language understanding. In addition, the OpenAI API's cloud-based nature provides scalability and access to powerful NLP features. By fine-tuning the GPT-3 model on the company's data, the chatbot will be better equipped to handle a wide range of NLP tasks related to the company's specific needs.

However, there are a few considerations to keep in mind. Integrating the OpenAI API will incur additional costs due to the usage-based pricing model. The company should carefully evaluate the costs and benefits to ensure this solution aligns with its budget constraints.

While using Rasa as the base framework offers data privacy, the company must also consider potential data privacy implications when using the OpenAI API. OpenAI's data usage policy should be reviewed to ensure compliance with the company's data privacy requirements. Though OpenAI claims they will not use data submitted by customers via API to train or improve models, data sent through the API will be retained for abuse and misuse monitoring purposes for a maximum of 30 days, after which it will be deleted (OpenAI, 2023).

By combining Rasa with the OpenAI API, the company can create a powerful, customised chatbot that addresses data privacy concerns and leverages advanced NLP capabilities for the effective handling of documented information such as manuals. However, the company should also consider the cost implications and data privacy aspects related to the OpenAI API integration before finalising this solution.

5. DISCUSSION

5.1. Key Findings

The key findings of the thesis reveal that each of the chatbot platforms exhibit unique strengths and limitations. Dialogflow and Microsoft Bot Framework excel in terms of ease of deployment and integration with their respective cloud ecosystems. Rasa, with its open-source framework, offers greater customization, flexibility, and control over data. IBM Watson Assistant characterises itself by providing pre-built content packs and comprehensive support for various industries. OpenAI API showcases cutting-edge NLP capabilities through the GPT-3 model, making it suitable for a wide range of natural language tasks. Data privacy is a crucial factor for the organization and should be carefully assessed when examining the available options.

5.2. Implications for Organisations

Selecting the right chatbot solution has significant implications for organisations, especially those dealing with sensitive data, such as training a chatbot on documented information such as manuals. The chosen solution should align with the organisation's data privacy requirements, costs, resources, customisation options, and existing infrastructure to provide the best value and functionality.

5.3. Addressing Challenges and Limitations

Organisations should be aware of potential challenges and limitations associated with implementing chatbot solutions, including data privacy concerns, integration with existing systems, and varying costs for usage or deployment. To overcome these challenges, organisations must carefully evaluate their needs, allocate appropriate resources, and choose a solution that balances functionality with costs and data security.

5.4. Ethics of Deploying a Chatbot

Deploying chatbots comes with ethical considerations that organizations must carefully address to ensure responsible and fair usage.

Chatbots often process sensitive user data, making it crucial for organizations to adhere to data protection regulations such as GDPR, HIPAA, and others. Proper data storage, encryption, and handling practices must be implemented to protect users' privacy. Users should also be informed when they are interacting with a chatbot instead of a human, allowing them to make informed decisions about the information they share and the actions they take based on chatbot responses.

Chatbots, as as any AI-driven technology, can inherit biases present in the training data. Ensuring that the chatbot does not discriminate against specific user groups or promote harmful stereotypes is an essential ethical consideration. This can be achieved by using unbiased training data and regularly monitoring and refining the chatbot's performance. Furthermore, obtaining user consent before collecting their personal information or preferences is essential. Users should have the option to opt-out of data collection and processing activities if they wish to do so.

Organizations should take responsibility for their chatbots' actions and potential consequences. A clear chain of accountability and a process for addressing user grievances or concerns related to chatbot interactions should be established. Because chatbots can potentially be manipulated for malicious purposes, such as spreading misinformation or abusive content. Organizations must implement safeguards to prevent misuse and monitor the chatbot's interactions for any signs of malicious intent.

While chatbots can provide a more human-like interaction, it is essential to recognize the ethical implications of over-emphasizing empathy or manipulating users' emotions. Striking a balance between helpfulness and emotional manipulation is crucial to maintain an ethical stance.

These ethical aspects should be addressed to deploy chatbots in a responsible and user-centric manner, ensuring that they contribute positively to user experiences without compromising their values or users' rights.

5.5. Key Changes in Human Interaction Due to Chatbot Deployment

Deploying chatbot technology can significantly alter the way people interact, both with technology and each other.

Chatbots provide immediate assistance, enabling users to access information or support 24/7. This can lead to people expecting faster response times and a higher degree of availability, which may influence their interactions with other service providers and their expectations from human-to-human communication.

Chatbots also encourage users to communicate more concisely, focusing on specific keywords or phrases to achieve the desired outcome. This trend can affect people's communication patterns, making them more direct and to the point resulting in streamlined communication.

In addition, chatbots can use data to deliver personalized experiences, which may lead people to expect more tailored interactions from both AI and human service providers. This shift in expectations could drive greater demand for personalized services in various industries.

Moreover, as chatbots become more prevalent, some individuals may interact less frequently with human service providers, potentially reducing the development of interpersonal skills or human connection in customer support and service contexts.

Hence, the convenience and efficiency of chatbots may lead to greater dependency on technology for everyday tasks and decision-making, impacting the way people seek information and approach problem-solving.

The more company adopts chatbot technology the more the possibility it could lead to job displacement in certain sectors, particularly those focused on customer service and support. As a result, employees may need to develop new skills and adapt to changing job roles or industries.

The increased use of chatbots may influence people's perception of trust in technology, particularly in situations where ethical concerns, such as privacy, fairness, and transparency, are paramount.

In the end, deploying chatbots can significantly change the way people interact by setting new expectations for availability, responsiveness, personalization, and technology reliance. These changes highlight the importance of considering the broader societal implications of chatbot deployment and ensuring that ethical concerns are addressed to maintain a positive impact on human interactions.

6. CONCLUSION

6.1. Final Thoughts and Answer to a Research Question

NLP chatbot technologies can revolutionize how companies manage information. Considering data privacy and the utilization of existing resources such as manuals for chatbot training, Rasa appeared as a fitting solution.

Rasa's open-source framework suits a company prioritizing data privacy, as it allows for greater control over their data with on-premise or cloud-based deployment options. It also provides extensive customization and flexibility, making working with specialized documented information such as manuals beneficial.

Rasa's open-source nature offers cost-effectiveness, with core functionalities accessible at no cost, although premium enterprise plans are available. It also supports flexible integration and deployment, aligning with a company's infrastructure. Active development and strong community support ensure the company benefits from continuous enhancements.

Alternatively, if exploring the OpenAI API, a custom chatbot using Rasa as a base framework and integrating OpenAI API could be considered. This approach combines Rasa's data privacy and customization capabilities with OpenAI's advanced language understanding. However, cost and data privacy concerns linked to the OpenAI API integration should be carefully considered. This solution would provide a tailored, powerful chatbot, addressing data privacy concerns, and effectively leveraging advanced NLP capabilities.

6.2. Recommendations for Future Research

Considering the constraints acknowledged in this research, the following areas of focus for future investigations are proposed:

- Practical Testing: Future studies should incorporate practical testing of identified NLP chatbot solutions. Hands-on testing could provide valuable insights into these solutions' usability, robustness, and real-world performance. Such testing might involve developing prototype chatbots using different platforms and subjecting them to a range of interaction scenarios.

- Extended Timeframe: Future research should be conducted over a longer period to collect and analyse more data. This could allow for a more comprehensive market analysis and evaluation of a broader range of chatbot solutions.

- Continuous Monitoring: Given the dynamic nature of AI and NLP technologies, researchers should continuously monitor advancements and updates to existing technologies. Studies should be updated or revisited periodically to ensure their findings remain relevant and applicable.

- Primary Data Collection: Future studies could incorporate primary data collection methods to avoid potential biases or inaccuracies from published sources. This could include conducting interviews or surveys with chatbot developers, vendors, or users. Researchers could also directly interact with chatbot platforms to gather first-hand information.

- Inclusion of More Chatbot Solutions: Future research should aim to include a wider range of chatbot solutions in the evaluation. This could help to provide a more comprehensive picture of the market and increase the generalizability of the findings.

- Long-term Impact Analysis: Future studies might also consider assessing the long-term impacts of chatbot implementation on organizational processes, customer satisfaction, and other key performance indicators. This could provide valuable insights into deploying chatbot technologies' enduring benefits and challenges.

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