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DESIGN AND EVALUATION OF A CONVERSATIONAL AI BOT FOR HELP DESK SUPPORT USING THE RASA FRAMEWORK AND DIET CLASSIFIER

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Abstract
The digital era has transformed customer service expectations, with users now demanding immediate, accurate, and continuously available support that traditional human-operated help desks struggle to deliver. This study presents the design, development, and evaluation of a Conversational Artificial Intelligence (AI) bot for help desk support, built on the open-source RASA machine learning framework and powered by the Dual Intent and Entity Transformer (DIETClassifier) for joint intent classification and entity recognition. The methodology combined stakeholder-driven requirements gathering, agile design and development, and iterative testing. The bot was trained for 100 epochs on a curated dataset of help desk interactions dominated by Windows operating system support queries, covering tasks such as system updates, boot and network troubleshooting, malware protection, password resets, file recovery, and disk and driver management. Results show that the transformer-based DIETClassifier accurately recognised and classified a wide range of user inputs, from simple greetings to elaborate technical questions, while the UnexpecTEDIntentPolicy provided robustness against atypical or out-of-scope queries. Initial testing demonstrated a considerable improvement in response quality over prior rule-based systems, with the bot maintaining conversational context across multiple turns. Interaction logs, however, revealed a degree of repetitiveness in generated responses, indicating scope for data refinement and more diverse response selection. Overall, the study demonstrates that a lightweight, framework-based conversational AI can substantially improve help desk efficiency, availability, and operational cost, while highlighting emotional intelligence, escalation to human agents, and data privacy as key areas for future enhancement.

1. INTRODUCTION

With the advent of the digital era, the ecosystem of customer service has undergone a substantial shift driven by technological progress and evolving consumer expectations. Where traditional support relied on human operators answering phone lines and emails, today's 24/7 service culture demands quick answers and prompt resolutions. Providing this level of responsiveness is difficult for human agents because of their limited availability and the variability in service quality, and organisations have therefore begun to search for creative alternatives (Salesforce, 2023).

The development of Artificial Intelligence (AI) technologies has opened new possibilities for handling large volumes of customer contact. AI assistants that mimic human communication are increasingly adopted to overcome the shortcomings of conventional help desks. These chatbots provide timely, consistent, and scalable answers to customer queries, allowing Customer Service Representatives to shed repetitive work and concentrate on more complicated aspects of customer service (Gupta et al., 2021; Huang et al., 2023). The main enabling tools are Natural Language Processing (NLP) and Machine Learning (ML) algorithms, which allow systems to understand queries, generate responses, learn from interactions, and improve continuously. The benefits include improved customer satisfaction through fast and accurate answers, more efficient operational processes, and reduced labour costs. Nevertheless, implementation faces challenges: bots must handle diverse demands with empathy, accuracy, and contextual awareness; high-quality data is necessary for model training; and successful deployment depends on integration with business systems and escalation paths to human agents when necessary.

1.1 Project Rationale

The basic rationale for constructing a conversational AI bot for help desk services is the rapid change in customer service expectations driven by AI innovation. Customers expect immediate, simple, round-the-clock support that traditional channels, operating with limited resources and time, cannot deliver. AI chatbots emerge as the most favourable solution: they autonomously process repetitive queries and tasks, freeing human personnel to deal with more complex problems beyond the chatbot's capacity. The project also supports the strategic objective of using technology to achieve high performance at low cost within organisations, translating into higher customer satisfaction and loyalty (Park et al., 2023; Sun et al., 2023).

1.2 Aim and Objectives

The central aim of the project is to considerably improve customer support services through the strategic implementation of a Conversational AI chatbot, overcoming the challenge of meeting consumers' demand for immediate access while diminishing the pressure on agents handling routine issues. This aim is broken into specific objectives: (i) a thorough evaluation of previous support requests to determine the most common queries clients make, enabling a customer-focused bot capable of handling the majority of frequently asked questions; (ii) the creation of the conversational chatbot using appropriate AI tools and programming languages, implemented in a user-friendly way and smoothly attached to existing customer service channels; (iii) an escalation capability that passes more complex issues to human experts so customers receive precise and appropriate help; (iv) testing and evaluation covering response accuracy, user satisfaction, and efficiency; and (v) collection of user feedback after deployment to analyse the chatbot's impact and recognise areas for improvement (Tang et al., 2023; Wang et al., 2022).

1.3 Conversational AI Bot

A conversational AI bot is a complex union of AI technologies that imitates human-to-human interaction through text or speech channels. At its core it applies NLP and ML to understand, interpret, and respond to user queries in a way that resembles human conversation, with capabilities ranging from simple question answering to serving many users in purchasing or customer support scenarios. In contrast to traditional rule-based chat robots, conversational AI bots learn from each interaction, improving their understanding and enhancing future conversations. They can therefore offer personal service to clients at any time, without the limitations imposed by human fatigue or unavailability, and through digital integration they can present relevant, situation-tailored information and solutions.

2. LITERATURE REVIEW

The AI industry is evolving rapidly, and conversational AI bots stand out as a promising technology, especially effective in customer service and support. AI-enhanced systems with NLP and ML capabilities are being deployed at help desks to maximise the customer service experience and improve operational effectiveness. Conversational AI at help desks improves productivity, accessibility, and customer service, boosting business through satisfied, loyal customers (Awan et al., 2023; Chen and Xie, 2023). Chatbots automate simple questions and repeatable activities so that human agents and customers spend more time resolving complex cases that need empathy and deeper insight, which improves resource allocation and can reduce operational costs (Al-Alawi et al., 2024; Luminita and Mocean, 2022).

Applications of conversational AI now span many domains. In healthcare, chatbots facilitate prompt dialogue between patients and providers, supporting appointment scheduling, medication adherence, and initial symptom assessment (Akash Goel et al., 2023; Poonam Tanwar et al., 2023), while studies of ChatGPT have examined its role in clinical assistance and medical education (Dylan Gracias et al., 2023; Yi Xie et al., 2023). In education, AI-powered frameworks such as Tayseer support technical and vocational student help desks and improve administrative efficiency (Abeer Alabbas and K. A., 2024; Islam Samih Mohamed et al., 2024). In banking, intelligent chatbots give clients 24/7 access to account information, transactions, and financial advice, improving engagement and business efficiency (Ajmeera Kira et al., 2023; Kim and J., 2021; Maharani and K. H., 2022). Agriculture has seen AI-driven bots that guide crop management and pest detection, helping farmers make judicious decisions (Poonkuzhali Ramadoss et al., 2023). Software development benefits from chatbots that assist with debugging, code suggestions, and routine tasks (Justine Winata Purwoko et al., 2023), and voice recognition chatbots extend these capabilities to consumer products (Kathirvelu et al., 2022). In customer service itself, deep neural network based chatbots and AI solutions have been surveyed extensively (Mohammad Nuruzzaman and O. K. H., 2018; Sarathsimha Bhattaru et al., 2024; Sousa, 2019), with self-learning bots adapting from user interactions and preferences (Parth Thosani et al., 2020) and comparative studies of chatbot versus human service examining customer perception and reuse intention (Sut Ieng Lei et al., 2021; Yang Cheng and H. J., 2021).

Despite this progress, important limitations remain. Current technology often lacks cognisance of the subtleties of human language, producing inaccurate responses or missing what the user intends to communicate. Providing emotional intelligence is a severe problem: in emotionally charged situations, chatbots struggle to show empathy and understanding. Security is a further challenge, since a bot processing sensitive personal and financial information becomes a potential target for attackers (Julija Skrebeca et al., 2021; Kandala Kalyana Srinivas et al., 2022). Ethical matters, including transparent algorithmic decision-making and fairness of AI-based interaction, must also be addressed (Taecharungroj, 2023).

Critically evaluating this body of work, conversational AI has reshaped organisations by merging technological achievement with practical, always-available support, which is essential in a world where urgent responsiveness is expected. Personalisation based on past interactions deepens satisfaction and customer retention, and self-service reduces the number of issues needing human attention. However, chatbots have not yet reached the level required to replace human experts in complex decision-making. The continued growth of AI and ML attests to the improving intelligence of chatbots, but the present downsides — natural language understanding, human emotion, data protection — must be resolved before the benefits are fully enjoyed. It is recommended that future improvements leverage machine learning to allow chatbots to show empathy through continuous learning, while securing user data and ensuring AI is used for the common good.

3. METHODOLOGY

The methodology adopts a systematic and practical approach to designing an intelligent human–machine interface for a help desk application. The core of the implementation is RASA, an open-source machine learning framework for building conversational applications, which implements NLP and uses the DIETClassifier to give contextual understanding of user sentences (RASA, 2020).

3.1 Requirements Gathering

The first stage defined the scope and objectives with precision, aiming for a chatbot that could successfully address routine customer inquiries with an excellent user experience. Stakeholder meetings, user feedback surveys, and analysis of current customer support channels were executed to reveal frequently asked questions, favoured information channels, and the characteristics of an ideal support desk environment. This phase also identified technical and operational bottlenecks, including system integration with existing customer service platforms, data protection compliance, and scalability concerns, providing a solid basis for the design and development phase.

3.2 Design and Development

Design began with a detailed analysis of user requirements and preferences, gathered by combing past support interactions across different channels and customer feedback. This analysis substantiated a detailed specification of the chatbot's purpose, interaction flows, and technical elements of the user interface. Development followed agile methodologies with iteration, refinement, and continuous testing, allowing feedback from early user testing to shape the implementation. A conversation management system was integrated to perceive user inputs, handle dialogue state, and utter contextually correct responses; the system connects to the organisation's knowledge base to retrieve and deliver information in a timely manner. Escalation mechanisms hand complex issues to human experts when automatic responses are inadequate, and data protection measures and adherence to privacy laws were treated as primary concerns throughout.

3.3 The RASA Framework

RASA encompasses two major components. RASA NLU (Natural Language Understanding) is responsible for understanding user input: it turns raw text into structured meaning by identifying the user intent (what the user really wants) and entities (useful data to be extracted). For example, in a travel booking bot the intent could be 'book flight' and the entities could be destinations, dates, or times. RASA NLU employs machine learning models trained on domain-specific datasets, augmenting the bot's comprehension over time (Rajpurohit, 2023). RASA Core handles conversation and dialogue flow management: it uses the NLU insights to formulate contextually aware responses and applies a machine learning model that predicts the next best action given the conversation history and current state, enabling networked and nonlinear conversations. RASA's extensible and scalable architecture integrates with different systems and APIs, and because it can be deployed on-premises or in a private cloud it keeps sensitive data protected, which is important for organisations with data governance and compliance requirements (RASA, 2020).

3.4 DIET Classifier

The DIETClassifier (Dual Intent and Entity Transformer) is a pivotal part of the RASA NLU module, comprehending user inputs by recognising intent and entities concurrently with a single model, making it highly resource-efficient (Saini, 2020). The architecture is Transformer-based, employing a lightweight self-attention mechanism that concentrates on the words most diagnostic of intents and entities in a sentence. Embedding layers transform words and sentences into numeric representations; these can use pre-trained word embeddings from models such as GloVe and fastText, or be learned from scratch, and optional character-level embeddings help handle spelling errors and out-of-vocabulary words. DIET is trained with a joint objective covering both intent classification and entity recognition, so both tasks are optimised simultaneously, producing more cohesive understanding and less contradictory behaviour. The algorithm is also optimised for the imbalanced data observed in real-world applications, where some intents or entities are more common than others, and it accepts sparse and dense input features (DIET, 2023).

3.5 Comparison with Alternative Models

Compared with LSTM (Long Short-Term Memory) networks, traditionally used for sequence modelling problems such as intent classification and entity recognition, DIET's self-attention mechanism processes input in parallel, improving training and inference speed, and its joint handling of intents and entities gives better contextual understanding than running two separate LSTMs (DIET, 2023; RASA, 2020). Compared with CRF (Conditional Random Fields), which are effective for entity and sequence tagging but require sophisticated feature engineering and do not perform intent classification, DIET accomplishes both tasks simultaneously and learns contextual interactions directly from text. Compared with BERT and related models such as DistilBERT and RoBERTa, which represent the state of the art in many NLP tasks, DIET's principal advantage is lightweightness: BERT models are heavy, straining RAM and computational power, which is problematic for low-resource environments, whereas DIET adapts to conditions with limited resources and can be trained from scratch without external data annotation. In cases where deep contextual comprehension is critical and large computational facilities are available, BERT can outperform DIET, so the choice depends on hardware, operating efficiency, and ease of use (RASA, 2020).

3.6 Model Training and Evaluation Approach

Default RASA parameter values were used, with configuration updates uncommented and applied where required. The classifier was trained for up to 100 epochs with appropriate confidence thresholds, ensuring a high-quality learning process while avoiding overfitting. The setting constrain_similarities = True was applied in the DIETClassifier configuration, enabling the classifier to learn clearer boundaries between differing categories during training and minimising ambiguous predictions. Evaluation was designed as a holistic process covering response accuracy, user engagement metrics, resolution times, and user satisfaction, alongside examination of the chatbot's NLP capability to decipher user intent, handle transactions of different formats, and hold multi-turn conversations. Operational impact was assessed by comparing pre- and post-implementation data such as human agent workload, average issue handling times, and cost per interaction (Du-Harpur, 2020).

4. RESULTS AND DISCUSSION

4.1 Training Data

In the chatbot's training data, Windows operating system issues were the most common category, reflecting the questions users typically ask when managing their computers. The compilation contains queries on updating Windows to the latest version, solutions for boot and network issues, protecting the computer against malware, and improving system performance, alongside everyday technical tasks such as resetting passwords, recovering deleted files, managing disk space, and handling driver and hardware problems. The generality and versatility of these questions train the chatbot to understand and respond to a wide range of technical issues across Windows tasks, delivering correct and accurate solutions to most technical queries raised. Figure 1 shows the composition of the training data.

```
How do I update Windows to the latest version?
What should I do if Windows won't start?
How can I reset my Windows password?
How do I check my Windows OS version?
How to troubleshoot network connectivity issues on Windows?
How can I recover deleted files in Windows?
What steps should I take to improve Windows performance?
How do I install or uninstall programs on Windows?
How to fix "low disk space" warning in Windows?
How do I manage privacy settings in Windows?
Why is my Windows running slow, and how can I fix it?
How to resolve driver issues in Windows?
How do I use System Restore in Windows?
How can I secure my Windows against viruses and malware?
How do I troubleshoot hardware issues on my Windows PC?
```

Figure 1: Training Data

4.2 Model Training Results

The DIETClassifier, configured to run its training over 100 epochs, demonstrated how chatbot technology blends the latest NLP capabilities. The system is predicated on the idea that determining user intent and identifying entities are not separate tasks but intertwined processes. Based on the transformer architecture, the classifier handled long sequences and extracted context across different conversation turns — particularly important for maintaining dialogue that is coherent and context-related, a necessary requirement for an excellent user experience. The training regime, with epochs logged in the configuration files and the number of epochs set above one hundred, gave the model enough instances to learn from while evading overfitting, and the constrain_similarities setting enabled the classifier to learn clear boundaries between categories, minimising the probability of ambiguous or mixed-up predictions. Figure 2 shows the model training output.


```
policies: null
# # No configuration for policies was provided. The following default policies were used to train your mod
# # If you'd like to customize them, uncomment and adjust the policies.
# # See https://rasa.com/docs/rasa/policies for more information.
#   - name: MemoizationPolicy
#   - name: RulePolicy
#   - name: UnexpecTEDIntentPolicy
#     max_history: 5
#     epochs: 100
#   - name: TEDPolicy
#     max_history: 5
#     epochs: 100
#     constrain_similarities: true
```

Figure 2: Model Training

After training, operations became more precise in recognising and accurately classifying a combination of user inputs, from common greetings to more elaborate questions. The system's timely and precise responses illustrate the efficiency of the neural network model powering it. The model architecture exhibits intrinsic robustness, enabling it to deal with repetitive intents that often cause problems in conversational AI, and the resilience of the agent is clear in the UnexpecTEDIntentPolicy, which watches for atypical or out-of-scope inputs.

4.3 Interaction Analysis

The chatbot's interaction history with users suggests that the texts produced are consistent but at times repetitive relative to users' inputs. Although the bot appropriately addresses and confirms what the user says, there is a low level of diversity in its responses, indicating potential for improvement. The monotony could be reduced through data refinement or by altering the response selection algorithm to produce more unique answers and a more diversified conversation. The logs also show that the bot can carry the dialogue without being distracted even through extended interaction loops, highlighting the constancy of the mechanism while suggesting a need for more sophisticated navigation routines. Figure 3 presents sample results from the deployed bot.

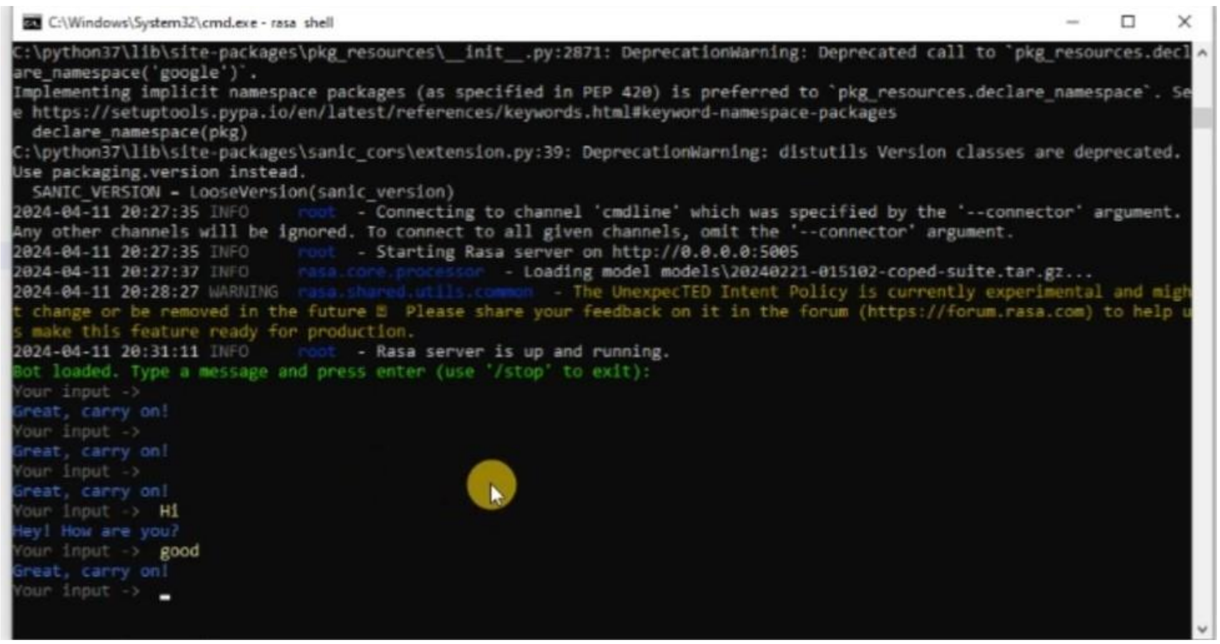

Figure 3: Results

Taken together, the configuration files and interaction logs yield a snapshot of a versatile system in action. The solution proves to be a multipurpose, state-of-the-art demonstration of how RASA skilfully deploys NLP capabilities to generate conversations that appear natural and efficient. Initial testing showed a considerable increase in response quality compared to prior rule-based systems, and users gave high ratings resulting from the bot's ability to follow context and remember previous interactions, enabling one-to-one communication. The results, however, can hardly be considered complete, as there is a continuing demand for improvement: expanding the training corpus to widen the bot's vocabulary, optimising the model's hyperparameters for larger precision, and adding advanced contextual understanding toward greater conversational maturity.

5. CONCLUSION AND RECOMMENDATIONS

This work developed an always-accessible, AI-monitored conversational bot system for help desk support. The mixed implementation of artificial intelligence, natural language processing, and machine learning made the chatbot capable of context-aware, continuous, and accurate interaction with human users. The innovation leads to quicker customer service responses, with human agents dealing only with hard-to-answer requests, contributing to strong operational efficiency. The AI's capacity to learn from past sessions provides a viable approach to emerging customer service issues. At the same time, the fundamental inability of AI agents to understand the full spectrum of complicated human emotions remains one of the main obstacles to AI systems fully replacing human interaction in customer service. The introduction of the AI chatbot has raised customer care indicators and made the help desk area more proficient, easing the road for similar applications in other fields and demonstrating how AI may transform traditionally static corporate functions into responsive, automated, and consumer-oriented models.

Several recommendations follow from the analysis. First, the chatbot's capacity to comprehend intricate user interactions should be increased using sophisticated NLP and ML algorithms, with consistent updates and training on varied datasets so the model adapts to new patterns and speech idiosyncrasies. Second, integration with existing customer service platforms must be smooth and robust, verified by compatibility checks and tests enabling seamless data exchange and unified functionality. Third, a more personalised approach is needed: chatbots should understand and respond to the unique needs of each customer using interaction and transaction history, with data analytics deepening the understanding of customer behaviour and preferences to increase satisfaction and loyalty. Fourth, escalation procedures must be incorporated so the bot recognises scenarios requiring a human agent and transitions the conversation smoothly without affecting customer experience. Finally, constant monitoring and evaluation, including regular testing and user feedback, should drive updates that enhance the chatbot's output and effectiveness. Future development should stress comprehension and conveyance of information, user-friendliness, personalisation, case escalation, and continuous feedback, alongside strengthening emotional intelligence and data protection mechanisms, so that AI chatbots remain a valuable asset in the continually changing customer service field.

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