GENERATIVE AI-BASED CHATBOT FOR CUSTOMER IT SUPPORT AUTOMATION

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Declaration

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Abstract

Managing customer queries efficiently is a pressing challenge for organizations like LOLC Bank, where decentralized systems result in communication delays, increased operational costs, and reduced productivity. The purpose of this study is to address these challenges by developing a Generative AI-based chatbot that automates customer support processes. This research investigates the inefficiencies of the current system and explores solutions for streamlining communication and automating repetitive tasks through AI-driven technology [1].

The main goal of this research is to create a chatbot that synchronizes well with LOLC internal procedures and responds to inquiries immediately while performing other repetitive tasks. The chatbot will be a centralized system that will provide the users with relevant and context sensitive information to minimize the workload and improve interaction and communication. Some of these are the ability to build a better interface by creating an avatar, building and updating a central and easily scalable knowledge base, the ability to generate responses with the help of artificial intelligence, and integration with internal forms and systems.

One of the major components of this work is the implementation of conversational form-filling automation, where the chatbot interacts with users in natural language to automatically populate forms. This feature aims to reduce user workload, minimize errors, and accelerate tasks such as submitting requests or retrieving information.

The proposed chatbot is expected to increase the efficiency of LOLC Company, decrease the time taken to solve queries and, in the process, increase user satisfaction thus allowing employees to attend to core business responsibilities thereby increasing productivity in the workplace.

Key Words*: GenAI, Conversational Ai, Natural Language Processing, Form Filling Automation, Conversational Form Filling, Large Language Models (LLMs), Microservices, Transform model, Open Source.*

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List of Abbreviations

IT - Information Technology

AI - Artificial Intelligence

GPT - Generative Pre-trained Transformer

GENAI - Generative Artificial Intelligence

LOLC - Lanka ORIX Leasing Company

NLP - Natural Language Processing

LLM - Large Language Model

DIET - Dual Intent and Entity Transformer

RAG - Retrieval-Augmented Generation

NLTK - Natural Language Toolkit

BERT - Bidirectional Encoder Representations from Transformers

NER - Named entity recognition

UI - User Interface

API - Application Programming Interface

JSON - JavaScript Object Notation

1. Introduction

1.1. Background

IT support is an essential service in current organizations as it makes workers continue their jobs without being halted by technical difficulties. Due to the constant need of businesses to rely on a digital infrastructure, effective IT support is now directly linked in terms of organizational productivity [2]. Any delay in resolving an issue like hardware failures, account access problems or server downtimes can also translate into substantial operation losses. To handle these demands, many businesses are turning to ticketing and service request processes that help to standardize and monitor problem resolution.

Today, organizations depend on online forms to collect information and handle service requests in the contemporary environment. However, form-based interfaces, a normality in most applications, pose serious usability problems. A broad survey concluded an array of frustrating experiences with confusing forms that users inevitably fill out incorrectly or not at all [3]. Further research conducted showed that 81% of users have left forms mid-completion when using the Internet, and that this was motivated majorly by issues of form complexity and confusion [4].

Technology is a core aspect of improving the quality of business transactions especially in reducing the effect of errors in business processes. In the words of Bataev and Davydov (2020), the integration of automation systems can greatly enhance the productivity of an enterprise through the reduction of manual work, exclusion of possible discrepancies, as well as the improvement of the general usability and experience for users [5]. In the context of customer service, automating the form filling process not only provides speed to interactions but also provides accuracy to the company which in return helps in providing better support services with time and money efficiency.

Conversational AI-based automated form-filling systems are gradually becoming innovative means of improving customer service . These systems help in cutting down the amount of work done by the users and improve the quality of the work by allowing the users to input information in form of natural language. The idea of this project is to design a conversational chatbot that can adaptively complete the form according to the customer interaction and is implemented in the context of IT support customer service.

The study takes this work forward and develops a conversational AI- enabled form-filling automation system within the setting of IT support services. The chatbot is something more than automation as it introduces flexibility and context sensitivity to make the interactions feel natural and flexible. Building on the recent advances in Natural Language Processing (NLP) and machine learning, the system will have the capability to parse various user inputs and formulate accurate suggestions as well as fill out support request forms with a high degree of efficiency. The outcome is to have a solution that will minimize form abandoning, will tolerate errors to the minimum, will facilitate the efficiency of IT support, and eventually enhance customer satisfaction.

1.2. Literature Review

The following literature survey is designed to review the previous studies and their methods and approaches to overcome the issues related to the AI based conversational automated form-filling system.

The process of filling forms is a critical part of most online procedures, but can be challenging depending on a person literacy or proficiency in a certain language. To support this issue, a number of studies have examined the use of conversational process of data collection using automated methodologies. The active use of chatbots as interactive interfaces to provide the necessary structured information to complete a form has already been noted by Meshram et al. [6], who showed how conversational AI can streamline the experience to a broader audience.

A research study titled "Exploring Large Language Models and Retrieval Augmented Generation for Automated Form Filling" (Research A) [7]. This research uses LLMs, GPT-3.5 in particular, together with Retrieval-Augmented Generation (RAG) for filling forms with appropriate output that is sensitive to the context of the input form. This is in reference to general purposes forms with integration to the real time web through a browser extension. RAG was employed in order to improve the model's context awareness, and the quality of the outputs was measured using BERT Score and G-EVAL. However, it is not specific to domains and does not include, for instance IT support workflow. It also offers very little in the way of unscripted conversational input, or free-form user engagement. In addition, multilingual and accessibility features are not discussed. The knowledge of LLMs and RAG lays the ground for conversational understanding and will be further expanded to IT-related situations in the present work.

Another research in the automated form-filling domain is "Automated government form filling for aged and monolingual people using an interactive tool" (Research B) [6]. This study introduced a Kannada voice-based chatbot called Dhvani to assist aged and monolingual users in completing government forms. The system relied on voice interactions for accessibility and incorporated a knowledge graph to determine scheme eligibility. However, it was limited to one regional language, Kannada, and offered a less dynamic or flexible workflow compared to natural human conversation. It did not support free-form inputs. While useful for accessibility, the approach does not scale well to technical fields such as IT support, which the present research seeks to address.

A work called "Bot Form Filler" (Research C) chatbot using Python to fill the forms is implemented with the help of libraries such as NLTK, spaCy & Selenium that are tailored for general-purpose web forms. Intent recognition and entity extraction are realized with traditional NLP approaches; Selenium is used for form filling [8]. However, the system is useful, it has a simple approach and does not support much of conversational inputs. It does not incorporate the features of advanced LLMs or domain specialties. The basic structure can be modified and implemented with further advanced NLP, and context awareness to meet the IT support scenarios.

A study titled "An Intelligent Framework for Auto-Filling Web Forms" (Research D) This framework employs context-aware solutions to predict and automatically fill web forms by employing clustering algorithms and analyzing user's interactions. In addition, such contextual information as locations, calendars, and semantic grouping of components are applied to increase

the accuracy [9]. However, the framework deals only with the structured data, and it does not have an element of real-time conversation. It is not tailored for domain specific processes and does not include provisions to deal with free text input, it does not include provisions for post-correction or feedback mechanisms. These contextual mechanisms may help to spur improvements in real-time or dynamic adaptation and work processes in the proposed work.

Another related work, "Artificial Intelligence Agent for Contextual Guidance in Form Filling" (Research E) [10], demonstrates the approaches to use semantic and structural analysis along with adaptive learning to help users to complete the enterprise forms. The study presents an AI agent that uses natural language processing, named entity recognition, and dynamic knowledge base to offer real time assistance, identify errors and validate forms. Despite the contextual awareness and personalization, the system is missing an autofill feature that automatically fills in forms based on the user's inputs or past data. In addition, the research does not cover conversational interfaces and is devoted to enterprise workflows, which prevents it from being used in unsupervised user interactions. Such restrictions explain the necessity of developing an AI-based form-filling system for IT support, in which the focus should be made on the dynamic conversation and contextual autofill capabilities.

The following research aims to fill these gaps by developing a new domain-specific conversational AI chatbot for IT support and requests cases. Based on the advanced LLMs, improved NLP approaches, and context-sensitive mechanisms, the system is expected to deliver real-time conversational support, increase the quality of data entry, and facilitate the completion of forms, and address accessibility and user experience.

The Below table 1.1 shows a comparison of research A, B, C, D and E with the proposed system for conversational form filling automation system.

1.3. Research Gap

Table 1 COMPARISON BETWEEN EXISTING SYSTEMS

Features	Research A	Research B	Research C	Research D	Research E	Propose System
Conversational Form Filling	✓	✓	✓	✗	✓	✓
Conversational NLP for Intent Extraction	✓	✓	✓	✗	✗	✓
Contextual Form Filling	✗	✓	✗	✓	✓	✓
Smooth Form Flow	✗	✓	✗	✗	✓	✓
Auto Filling Feature	✓	✓	✓	✓	✗	✓
Adaptive Slot Filling	✗	✗	✗	✗	✗	✓
Semantic Ticket Classification	✗	✗	✗	✗	✗	✓
Contextual Suggestion (LLM-assisted)	✗	✗	✗	✗	✗	✓

Summary of Gaps Identified

The reviewed papers reveal that significant advances were made in automated form-filling, although there are still many gaps. All the existing systems are general-purpose or government related systems without a deep focus on the specifics of a given domain; in this case, IT support. The conversational aspect is poor because most strategies are focused on fixed work flows, scripted conversations or tied-down inputs as opposed to free flowing conversations. Those works that include contextual knowledge tend to be confined to formal data rather than loose derivations and do not support texts that suddenly vary to adapt to a personal history or domain knowledge. The use of advanced language models including GPT has been investigated but has not been applied in IT workflows where contextual clarification and technical precision are important. There are

autofill mechanisms, but they are usually not combined with conversational guidance and real time correction. Furthermore, all reviewed papers fail to deal with semantic ticket classification, which is fundamental to assigning IT support cases to categories, as well as offer an LLM-assisted contextual suggestion that helps to guide or confirm the input. Accessibility is also quite limited meaning that some solutions are locked to a specific regional language or even user pool hence they cannot be expanded to broader enterprise scenarios. Such gaps also demonstrate the necessity of having a domain-specific conversational AI system that integrates the use of the more advanced LLMs, contextual reasoning, semantic classification, and autofill capabilities to provide a more adaptable and effective conversational AI approach to IT support.

The proposed solution offers a conversational AI-based system that would automate filling out the forms on IT support requests. Current conversational systems that are aimed at form-filling tend to be based on asking many explicit questions, this inevitably adds user fatigue and causes them to abandon their task. They fail to maximize the tradeoff between the amount of questions and thoroughness of the final form. This gap, which this research seeks to fill, "Adaptive Slot Filling" involves being able to answer as many slots as possible with as few questions as possible by making use of semantic meaning, contextual inference, and predictive completion. This strategy minimizes repetition and time taken during the interactions and results in higher completion levels than computerized or fixed style chatbots. Dynamic dialogue in the system captures the input of the user, which is then predicted based on the type and category of tickets through semantic similarity, and recommendations of subject the support request ticket are given with the help of LLM. A priority detection system uses both keyword and semantic analysis to determine the priority of the support request, and there are business rules and user confirmation so that it is accurate. The outputted tickets are in JSON format and can be integrated using API and allow fully automated, context-driven and efficient IT support operations.

1.4. Research Problem

As for the service request forms at LOLC, users are in a way challenged when it comes to filling them due to confusion, lack of knowledge or ignorance of the information that is required. This leads to time loss, delays and at times incomplete or wrong documents being submitted to the intended recipients. Manual creation of forms is still a practice, which contributes to extra time and effort needed to fill in service requests. A study pointed out that form complexity affects the level of frustration of the users and there are typical mistakes that people make when filling forms, such as not reading the instructions, not being detailed enough and not explaining the importance of the project [11], [12]. In the same manner, form filling is always regarded as a task that consumes much time and is boring [4], [3], which results in incomplete or incorrect data entries submissions.

A survey found that 81% of people discontinue filling out an online form midway through the process, and 67% of those who encounter difficulties abandon the process entirely [13]. In the business world, forms are crucial for organizing and standardizing data, with 59% of U.S. workers regularly required to use forms in their jobs [14].

The overall rates of form abandonment are increasing because of several reasons such as complicated and long forms, where the users spend much time and the forms are complex, and where the users are not very sure of the information, they require to fill in the form they end up filling the wrong information.

These challenges make it clear that it is time to move beyond the limitations of traditional form-filling methods. As requested by LOLC, the goal is to develop a solution that not only simplifies the form-filling process but also facilitates faster completion when users are unsure of what information is required. This research recommends creating a conversational AI-based chatbot integrated into the IT support form submission system. The chatbot will assist users by identifying the required information through conversation and utilizing a knowledge base when necessary. This solution will help complete the necessary fields, improving the quality and completeness of the input data, and reducing the time users spend on the forms.

The main goal of the current research is to contribute to the optimization of the form-filling process, decrease the time spent on it, and increase the level of user satisfaction through the facilitation of interaction. In order to reduce the number of errors made by users while filling in the forms and to reduce the cases of form abandonment, the study aims to improve the efficiency of the IT support system through developing a conversational AI chatbot.

1.5. Research Objectives

1.5.1. Main Objective

The research objectives are realistic and specific targets that put into words what the research project seeks to accomplish. These are the objectives of the research, and all objectives should be SMART, that is Specific, Measurable, Achievable, Realistic, and Time-bound in order to make assessment of the outcomes easier.

The main goal of the research is to develop and introduce a conversational AI based chatbot that helps to automate the IT support form-filling procedure, minimizing the amount of time spent, errors, and frustrating the user. LOLC request forms are perceived to be complex and many customers do not know what they are required to provide. Not only does this cause delays and incomplete submissions, but also poses an extra burden on IT support staff's time which will have to be spent in clarifying the details manually. With the transition out of traditional and static forms into a more intelligent, conversational system, the intention of the system will be to increase its ease factor by a induced feeling of direction and guided experience on the part of the user.

To accomplish this objective, the chatbot is implemented based on Rasa open-source framework [15] , custom forms and rules-based response to conversational loops. The system has been trained to know user intents and extract a relevant information with natural language inputs. Semantic classification The classification problem is solved by semantic classification using transformer-based sentence embeddings, automatically predicting the type and category of the request on the basis of free-text user queries. Contextual support is also offered in the language model which

proposes the right topics and descriptions regarding the user issue and thus removes ambiguity and increases ticket clarification.

The unique feature of the research goal is to maximize the efficiency of form filling through adaptive slot filling, which aims to complete the maximum number of required fields with the minimum number of user queries by leveraging contextual inference and semantic understanding. As opposed to traditional infrastructures where asking a predetermined group of questions occurs, the proposed solution limits the repetitive nature through semantic inference, contextual reasoning and predictive completion. Consequently, the chatbot will interact with the fewest number of clicks with the highest number of fully filled fields with little explicit queries, limited user fatigue, and high-level accuracy. Besides, a hybrid priority detection mechanism was introduced that enables automatic assessment of the urgency of demands based on the combination of keyword-based rules and semantic analysis. This makes sure that important issues are not overlooked and users have the choice of accepting/rejecting system recommendations.

The drive towards the ultimate objective is to identify and provide the system that will improve form completion responses, data quality and integrate with the existing IT support operations. The chatbot provides in JSON format structured ticket data, which can be then integrated with any system through an API. With greater efficiency in responsiveness, elimination of manual intervention, and an overall smoother experience, the work helps the organization and end users as well. The goal is not only to demonstrate the viability of this sort of approach but also to point at the general importance of conversational AI in solving long existing inefficiencies in enterprise support systems.

1.5.2. Sub Objectives

Following the main objective of developing a robust, intelligent, and user-friendly conversational AI system for IT support form submissions, a series of sub-objectives has been defined. These sub-objectives ensure that the system conducts automated form-filling efficiently while imitating the guidance and decision-making of human support staff, maintains flexibility in handling diverse user inputs, and provides a smooth, accurate, and transparent interaction experience. Specifically, the logic for form filling has been designed to activate and deactivate the form loop based on user intent, dynamically adapt questions to fill the maximum number of slots with minimal queries, and validate responses before final submission. This structured approach allows the system to collect complete and precise data while minimizing user fatigue and errors, ultimately enhancing both user satisfaction and operational efficiency.

Chat UI Design

The first sub-objective is to design a user-friendly and responsive chat interface, implemented using React. This interface serves as the primary interaction point between users and the system, providing a guided conversational experience for IT support requests. The chat UI displays messages from both the bot and the user, prompts for additional information when needed, and supports options for users to confirm or modify suggestions provided by the chatbot. The design also incorporates feedback messages for validation, errors, and priority recommendations, ensuring a seamless and intuitive interaction for users unfamiliar with the form requirements.

Filling the Form Based on a Conversation

The conversational form filling process represents a paradigm shift from traditional static forms to dynamic, intelligent data collection through natural dialogue. This approach transforms the rigid question-and-answer format into an intuitive conversation where users describe their IT issues in their own words, while the system intelligently maps this information to the required form fields. The process begins when a user initiates a support request with a natural statement like "my mouse is not working," which triggers the system's conversational form loop that remains active until all necessary information is collected.

The system employs Rasa's custom form implementation with sophisticated slot-filling mechanisms that adaptively collect information based on the conversation context. Rather than following a predetermined sequence of questions, the chatbot dynamically determines which information is still needed and asks relevant follow-up questions in a natural flow. For instance, after the initial problem statement, the system automatically predicts the request type and category using semantic similarity, then intelligently asks for additional details like "Can you describe the trouble you are having?" The form filling process is enhanced by contextual reasoning, where the system understands the relationship between different pieces of information and can infer certain fields from user responses without explicitly asking for them.

A key innovation in this approach is the hybrid confirmation system that balances automation with user control. When the system generates suggestions for form fields like subject lines or descriptions using LLM assistance, it presents these to users for approval with options to "Keep this suggestion" or "Provide my own." This ensures accuracy while reducing user effort. The conversational form also implements progressive disclosure, revealing form fields gradually as the conversation unfolds, which prevents users from feeling overwhelmed by lengthy forms. The entire process maintains conversation state and context, allowing users to provide information in any order while the system intelligently organizes it into the proper form structure, ultimately creating a more natural and efficient user experience compared to traditional form interfaces.

Interruption Handling & Out-of-Scope and Unclear Message Management

The system implements robust interruption handling and comprehensive message management mechanisms to maintain conversational flow and user experience during the form filling process. For unclear message management, the system utilizes Rasa's Fallback Classifier with a confidence threshold of 0.63 and an ambiguity threshold of 0.2, which automatically detects when user inputs have low confidence values or are ambiguous, triggering clarification workflows that ask follow-up questions or provide specific examples to guide users toward providing the necessary information. When users provide inputs that don't directly answer the current question or are insufficient, the Fallback Classifier identifies these low-confidence scenarios and initiates predefined responses that help users understand what information is expected, maintaining conversational flow without breaking the form loop.

For out-of-scope interruption handling, the system employs specially trained NLU models that recognize non-IT related queries, general chitchat, or irrelevant interruptions through dedicated intent classification. Rasa's rule-based interruption handling allows users to ask clarifying questions, request help, or modify previously provided information while preserving the conversational state, ensuring users can seamlessly return to where they left off in the form filling process. When out-of-scope messages are detected, the system uses predefined fallback responses that politely acknowledge the input and redirect users back to the support request process, while unclear or ambiguous messages below the confidence threshold automatically trigger clarification prompts with multiple-choice options or rephrased questions. This comprehensive approach ensures that the conversational form remains resilient to unexpected user behavior, unclear communication, and off-topic interactions while maintaining the natural dialogue feel, preventing user frustration and form abandonment that commonly occurs in traditional rigid form interfaces.

Extract Relevant Information (Intent and Keywords)

The system's ability to extract relevant information from user inputs is fundamental to accurate form filling and relies on Rasa's sophisticated Natural Language Understanding (NLU) pipeline. To achieve precise intent recognition and keyword extraction for IT support scenarios, the system is trained with comprehensive example data that covers various IT support requests including hardware failures, software issues, account problems, and system outages. This training data encompasses diverse phrasings and technical terminology commonly used by employees when reporting IT issues, ensuring the model can understand both formal and colloquial expressions of technical problems.

The NLU pipeline employs several specialized components that work together to process and understand user inputs. The Whitespace Tokenizer serves as the foundation by breaking down user messages into individual tokens based on whitespace, creating the basic units for further analysis. The DIET Classifier (Dual Intent and Entity Transformer) acts as the core component, simultaneously performing intent classification and entity extraction using transformer-based architecture to capture contextual relationships between words. RegexFeaturizer enhances the system's ability to identify specific patterns such as error codes, IP addresses, device models, or structured identifiers commonly found in IT support requests. The LexicalSyntacticFeaturizer adds grammatical and syntactic understanding by analyzing part-of-speech tags and dependency relationships, helping the system distinguish between different types of technical terms and their roles in sentences. Finally, the CountVectorsFeaturizer creates numerical representations of text by counting word occurrences, providing statistical features that improve intent classification accuracy. This comprehensive pipeline ensures that the system can accurately identify user intentions, extract relevant technical details, and understand the context of IT support requests, forming the foundation for intelligent form completion and appropriate response generation.

Designing the Logic for Form Filling

The form filling logic represents the core intelligence that orchestrates the entire conversational process, determining when to collect information, how to handle user responses, and when to transition between different conversation states. The system employs Rasa's rule-based

architecture to define specific triggers and conditions that govern form activation, deactivation, and progression. The primary logic begins with intent recognition, where the detection of a "support_request" intent automatically activates the custom form loop, ensuring that once a user expresses the need for IT support, the system seamlessly transitions into information collection mode without requiring explicit commands or navigation. The form incorporates sophisticated state management that tracks which slots have been filled, which information is still required, and how to prioritize the collection sequence based on conditional branching logic that adapts the conversation flow based on previously collected information.

A critical aspect of the form logic is the implementation of slot validation and error recovery mechanisms that ensure data consistency and completeness throughout the conversation. When users provide ambiguous or incomplete information, the system employs clarification strategies, asking follow-up questions or providing examples to guide users toward providing the necessary details. The logic also incorporates interruption handling rules that allow users to modify previously provided information or ask questions without breaking the form flow, while implementing completion criteria logic that determines when sufficient information has been collected to generate a complete ticket. This intelligent logic ensures that the conversational form maintains a natural dialogue feel while systematically collecting all required information with maximum efficiency and minimum user friction, ultimately triggering the final confirmation and submission sequence when all necessary data has been gathered.

Implement the Form Filling Process and Automate Form Filling

To realize automated form filling, the system leverages Rasa’s slot mechanism to store and track user-provided information throughout the conversation. Each slot represents a specific field in the IT support form, such as request_type, category, subject, description, or priority. As the user interacts with the chatbot, their responses are captured by custom actions or Rasa NLU, and the corresponding slots are populated automatically.

The slot values serve as temporary memory for the chatbot, allowing it to maintain context, verify previously collected data, and adapt subsequent questions dynamically. By using slot mappings and conditional logic, the system determines which slot still requires input and asks targeted, context-sensitive questions. This approach reduces redundancy, avoids unnecessary questions, and ensures that each interaction maximizes the number of completed form fields while minimizing user effort.

Once all required slots are filled, the chatbot validates the collected information, confirms accuracy with the user, and compiles the form data into a structured format (JSON). This structured output can then be seamlessly integrated with external IT support systems via an API, completing the automated form-filling process with high efficiency and accuracy.

Validation Process

The system employs Rasa's FormValidationAction to ensure data quality and completeness throughout the conversational form filling process, implementing comprehensive validation logic for each form field before proceeding to the next step. FormValidationAction serves as a custom

action that is automatically triggered whenever a user provides input for any slot in the form, allowing the system to validate the extracted information against predefined criteria and business rules specific to IT support requirements. For each form field, the validation process checks data format, completeness, and logical consistency - for example, validating that extracted hardware names match known device types, ensuring priority levels align with detected issue severity, or confirming that descriptions contain sufficient technical detail for proper ticket processing.

When validation fails for any field, the FormValidationAction triggers specific error handling responses that explain what information is needed and provide examples to help users provide valid input. For instance, if a user provides an unclear description like "it's broken," the validation process detects insufficient detail and prompts for more specific information such as error messages or troubleshooting steps attempted. The system also implements cross-field validation to ensure logical consistency between related form fields, such as verifying that the predicted request type aligns with the user's description and priority level, ensuring all submitted tickets contain accurate, complete information for efficient resolution.

Final Submission

The final submission process provides users with a comprehensive ticket preview that displays all collected and auto-generated information in a structured format, allowing them to review and confirm the accuracy of their support request before committing to submission. Once all required form slots have been validated and filled, the system presents a complete summary showing the request type, category, subject, description, priority level, and user details in a clear, organized manner that mirrors how the ticket will appear in the IT support system. This preview stage serves as a final quality checkpoint where users can verify that the conversational AI has accurately captured their issue and requirements, with options to make last-minute modifications or corrections if needed before proceeding with the submission process.

Upon user confirmation, the system automatically compiles all validated form data into a structured JSON format that contains all necessary fields required by the target IT support system, ensuring seamless integration through API calls. The JSON output includes standardized field names and properly formatted data that can be directly consumed by existing service desk platforms without requiring additional processing or transformation. The API integration enables real-time ticket creation in the organization's IT support system, providing users with immediate confirmation of successful submission along with ticket reference numbers for future tracking. This automated submission process eliminates manual data entry by IT staff, reduces processing delays, and ensures that tickets are immediately available in the support queue with all relevant information properly categorized and prioritized for efficient resolution.

2. Methodology

2.1. Methodology

This research project aimed to develop a conversational form-filling system to automate customer support ticket creation. Instead of requiring users to navigate complex web forms, the system allows them to describe their problems in natural language, from which structured and properly categorized support tickets are generated.

My approach involved several key steps that I'll detail in this section. First, I had to choose the right tools and frameworks for building a chatbot that could understand technical language. Then I needed to design conversation flows that felt natural while still collecting all the necessary information. The biggest technical challenge was getting the system to automatically categorize issues and suggest appropriate priority levels without human intervention.

The entire solution uses artificial intelligence techniques including natural language processing and semantic similarity analysis. I also integrated a large language model to generate professional-sounding ticket subjects automatically. Each of these components required careful testing and tuning to work together effectively.

Research Design and Approach

Methodological Framework

This study employs a design science research methodology, focusing on creating and evaluating an innovative technological artifact - a conversational AI system for automated form processing. The research follows an iterative development approach where each component is built, tested, and refined based on performance outcomes and user interaction patterns.

The methodology combines quantitative evaluation of system accuracy with qualitative assessment of user experience factors. This mixed-methods approach ensures that the final system not only performs technical tasks correctly but also provides a satisfactory user experience that would be acceptable in real-world deployment scenarios.

Problem Definition and Scope

The research addresses the specific problem of inefficient customer support ticket creation processes. Traditional web forms often frustrate users and result in incomplete or poorly categorized support requests. The scope of this project focuses on creating an intelligent conversational interface that can automatically extract structured information from natural language descriptions of technical problems.

The system is designed specifically for IT support scenarios, where users report hardware malfunctions, software issues, network problems, and access difficulties. This focused domain allows for specialized optimization while providing a foundation that could be adapted to other support categories in future work

Selection of Frameworks and Tools Evaluation

Rasa Open-Source Framework

Understanding Conversational AI

Conversational Artificial Intelligence (CAI) represents a sophisticated branch of AI technology that enables natural language interactions between humans and computer systems. According to IBM (2023), conversational AI combines natural language processing (NLP), machine learning, and contextual awareness to understand, process, and respond to human language in a way that simulates human conversation [16]. This technology has evolved from simple rule-based chatbots to sophisticated systems capable of understanding context, maintaining conversation state, and performing complex tasks through natural dialogue.

The core components of conversational AI include Natural Language Understanding (NLU) for interpreting user intent and extracting entities, Dialogue Management for maintaining conversation flow and context, and Natural Language Generation (NLG) for producing human-like responses. Modern conversational AI systems also incorporate machine learning algorithms that enable continuous improvement through user interactions and feedback loops.

What makes conversational AI particularly powerful is its ability to make technology accessible to everyone. Instead of forcing users to learn complex interfaces or navigate through multiple screens, conversational AI allows people to simply describe what they need in their own words. This natural interaction style is especially valuable in customer support scenarios, where users are often frustrated and need immediate, intuitive assistance.

Comparative Framework Analysis

I evaluated several conversational AI frameworks before selecting the final technology stack. The evaluation criteria included technical capabilities, deployment flexibility, data privacy considerations, cost factors, and customization potential.

Cloud-Based Solutions Evaluation:

- Google Dialogflow offered ease of use and powerful pre-trained models but limited customization and required sending data to external servers
- Microsoft Bot Framework provided enterprise features but had complex licensing requirements and vendor lock-in concerns
- Amazon Lex integrated well with AWS services but lacked the fine-grained control needed for specialized form automation

Open Source Alternatives:

- Botpress provided a visual interface but limited natural language processing capabilities
- Rasa Open Source offered complete control and customization but required more technical expertise
- ChatterBot was simple to implement but lacked the sophistication needed for complex form automation

Framework Selection Rationale

The selection of Rasa Open Source as the primary conversational AI framework was driven by comprehensive background research into available conversational AI platforms and their suitability for

enterprise-grade form automation systems. After evaluating multiple options including cloud-based solutions like Google Dialogflow, Microsoft Bot Framework, and Amazon Lex, Rasa Open Source emerged as the optimal choice for this research project.

Open Source Advantages: Rasa's open-source nature provides unprecedented transparency and control over the underlying algorithms and data processing mechanisms. Unlike proprietary cloud-based solutions, Rasa allows complete customization of the NLP pipeline, dialogue policies, and response generation mechanisms. This transparency is crucial for enterprise applications where understanding system behavior and ensuring compliance with data governance requirements are paramount.

Scalability and Performance: Rasa's architecture is designed for production-scale deployment with support for horizontal scaling, load balancing, and distributed processing. The framework's ability to handle thousands of concurrent conversations while maintaining sub-second response times makes it suitable for enterprise customer support environments where performance and reliability are critical.

Full Customization Capabilities: The framework provides complete control over every aspect of the conversational experience, from custom NLU pipelines to sophisticated dialogue management policies. This level of customization is essential for developing specialized form automation components that must integrate seamlessly with existing enterprise systems and workflows.

RASA Technical Architecture and Components

Rasa NLU Pipeline Architecture

The Natural Language Understanding pipeline in Rasa processes user input through a series of configurable components, each responsible for specific aspects of language understanding. The pipeline configuration in the project's configuration file for a Rasa project demonstrates a carefully orchestrated sequence of processing steps:

Pipeline Component Analysis:

1. **WhitespaceTokenizer**: The initial tokenization process splits user input into individual tokens based on whitespace boundaries. This fundamental step prepares the text for subsequent feature extraction and analysis. The tokenizer handles various edge cases including punctuation, special characters, and multi-word expressions commonly found in technical support requests.

2. **RegexFeaturizer**: This component extracts features based on regular expression patterns, enabling the system to recognize structured information like error codes, IP addresses, software versions, and other formatted data commonly found in IT support requests. The regex patterns can be customized to match domain-specific terminology and formatting conventions.

3. **LexicalSyntacticFeaturizer**: This advanced component analyzes the grammatical and syntactic structure of user input, extracting features related to parts of speech, dependency relationships, and linguistic patterns. This analysis is particularly valuable for understanding complex technical descriptions where grammatical structure provides important context clues.

4. **CountVectorsFeaturizer**: Implemented with two configurations in the pipeline, this component creates numerical representations of text using count-based vectorization. The first instance uses word-level analysis, while the second employs character n-gram analysis (1-4 character sequences) to capture morphological patterns and handle misspellings common in user-generated content.

5. **DIETClassifier:** The Dual Intent and Entity Transformer classifier represents the core machine learning component responsible for intent classification and entity extraction. Configured with 150 training epochs and similarity constraints, this transformer-based model provides state-of-the-art performance for understanding user intentions and extracting relevant entities from technical support requests.
6. **EntitySynonymMapper:** This component normalizes extracted entities by mapping synonymous terms to canonical forms, ensuring consistent entity representation throughout the system. This is particularly important for technical support where users may refer to the same component using different terminology.
7. **ResponseSelector:** Configured with 150 epochs and similarity constraints, this component handles response selection for retrieval-based dialogue components. While not directly used in the form automation workflow, it provides foundation capabilities for handling FAQ-style interactions.
8. **FallbackClassifier:** The final component in the pipeline handles cases where the system cannot confidently classify user intent. With a confidence threshold of 0.63 and ambiguity threshold of 0.2, this component ensures graceful handling of unclear or out-of-scope inputs.

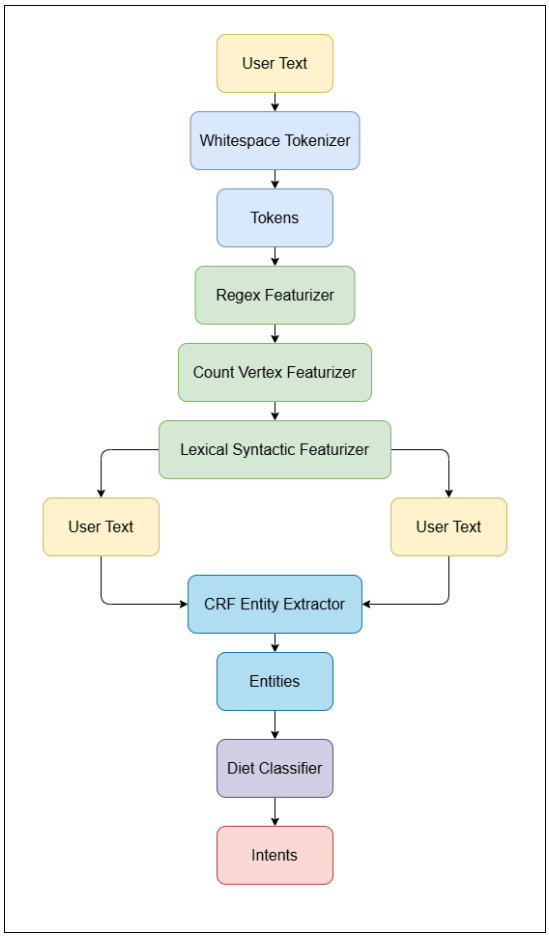

Figure 1 : Working of the RASA NLU pipeline

Rasa Core Architecture and Dialogue Management

Rasa Core handles the conversational flow and dialogue management through a sophisticated policy-based system that determines appropriate responses based on conversation context and system state.

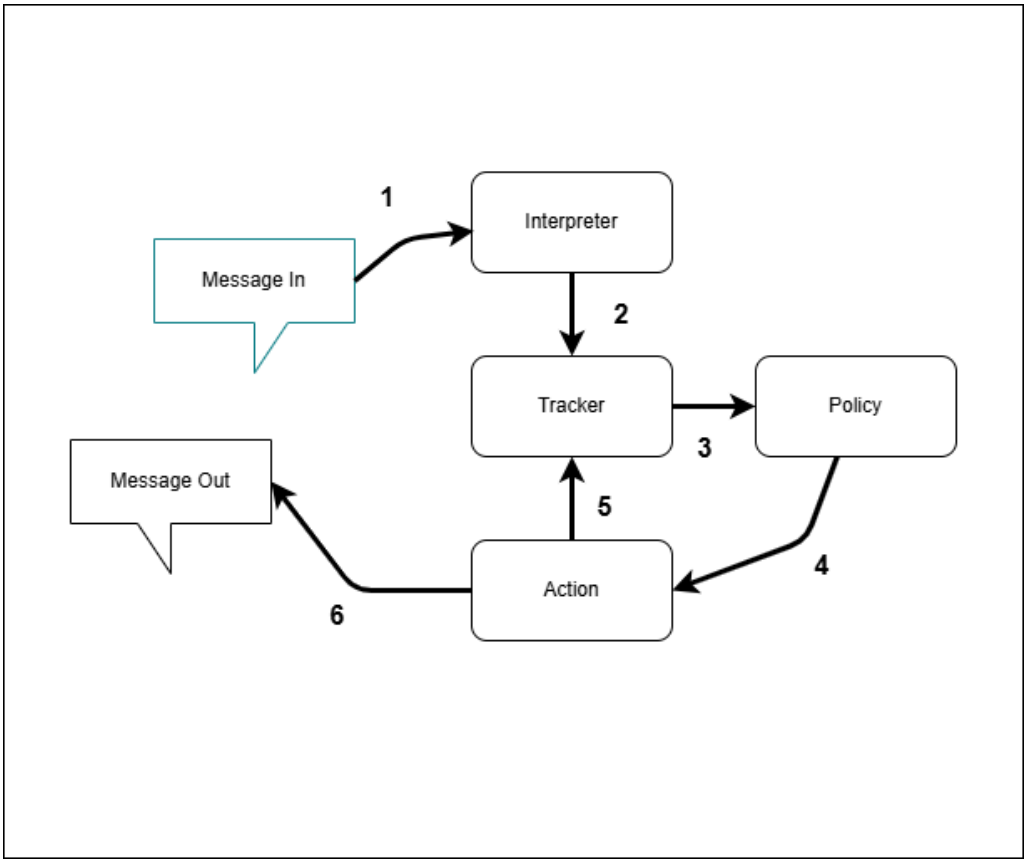

Figure 2 : Working of RASA core

Core Component Flow Analysis:

1. **Message Input Processing**: User messages enter the system through the message interface, triggering the conversation processing pipeline.
2. **Interpreter**: The NLU pipeline processes the incoming message, extracting intents, entities, and confidence scores that inform subsequent dialogue decisions.
3. **Tracker**: The conversation tracker maintains complete conversation state, including slot values, previous actions, and conversation history. This persistent state enables context-aware responses and complex multi-turn interactions.

4. **Policy System**: Multiple policies evaluate the current conversation state and determine appropriate next actions. The policy ensemble combines recommendations from different policy types to make optimal decisions.
5. **Action Execution**: Selected actions are executed, potentially updating conversation state, calling external APIs, or generating user responses.
6. **Message Output**: The system generates and delivers responses to users, completing the conversation cycle.

Policy Configuration and Dialogue Management

The system employs multiple complementary policies to handle different aspects of conversation management

Policy Detailed Analysis:

1. **MemoizationPolicy**: This policy handles exact conversation pattern matching, ensuring consistent responses for previously encountered conversation sequences. It provides reliable handling of common interaction patterns and maintains response consistency across similar conversation contexts.
2. **RulePolicy**: The rule-based policy handles deterministic conversation flows defined in the rules configuration. This policy is essential for form automation workflows where specific conversation sequences must be followed to ensure complete data collection.
3. **UnexpecTEDIntentPolicy**: This machine learning-based policy handles unexpected user intents and conversation interruptions. With a 5-turn conversation history and 100 training epochs, it learns to appropriately respond to user inputs that don't follow expected conversation patterns.
4. **TEDPolicy**: The Transformer Embedding Dialogue policy provides sophisticated context-aware dialogue management using transformer architecture. Configured with similarity constraints and extensive training, this policy handles complex conversation flows and context-dependent response selection.

Domain Configuration and Knowledge Representation

The domain configuration serves as the foundational blueprint that defines the operational universe of the conversational AI system. In Rasa, the domain file acts as a comprehensive specification document that establishes the boundaries, capabilities, and behavioral parameters within which the assistant operates. This configuration fundamentally determines what the system can understand, remember, and communicate during user interactions [15].

Conceptual Framework of Domain Definition:

The domain represents the complete conversational ecosystem, encompassing all possible interactions, data structures, and response mechanisms that the system can employ. It functions as both a constraint mechanism that prevents the system from operating outside defined parameters

and an enablement framework that provides the necessary components for sophisticated conversation management.

For the form automation system, the domain configuration is particularly critical as it must support structured data collection while maintaining natural conversational flow. The domain must accommodate the dual requirements of systematic information gathering and flexible user interaction patterns that characterize effective customer support experiences.

Response Architecture and Template Management:

Responses in the domain configuration function as templated communication mechanisms that ensure consistent, professional, and contextually appropriate interactions with users. These responses serve multiple purposes within the conversational framework, acting simultaneously as user communication tools and system action components.

The response system supports sophisticated messaging capabilities that extend far beyond simple text responses. Rich content integration enables the inclusion of interactive elements such as buttons for user selection, images for visual clarity, and custom JSON payloads for complex data transmission. This multimedia approach is particularly valuable in technical support contexts where visual aids and structured choices can significantly enhance user understanding and interaction efficiency.

Each response is inherently actionable within the dialogue management system, meaning that responses can be directly invoked as action steps within conversation flows. This dual nature of responses as both communication tools and system actions enables seamless integration between user communication and system behavior, facilitating smooth conversation progression and state management.

For the form automation component, responses are carefully crafted to guide users through the information collection process while maintaining engagement and clarity. Confirmation responses, validation messages, error communications, and progress indicators are all defined within the domain to ensure consistent user experience throughout the form completion journey.

Slot Architecture and Memory Management:

Slots represent the conversational memory system that enables the assistant to maintain context, store user-provided information, and track conversation state across multiple interaction turns. This memory mechanism is fundamental to form automation functionality, as it provides the persistent storage required for collecting, validating, and managing user data throughout the form completion process.

The slot system operates as a sophisticated key-value storage mechanism that accommodates both user-provided information and system-generated data. User-provided information includes direct responses to form questions, such as problem descriptions, contact details, and preference selections. System-generated data encompasses automatically derived information such as predicted issue categories, calculated priority levels, and conversation state indicators.

Form Creation and Structured Data Collection:

Form creation within the domain configuration establishes the framework for systematic information gathering through conversational interactions. The form structure defines required data fields, validation parameters, and collection sequences that guide the conversation toward complete information capture.

The form definition process involves specifying slot mappings that determine how user input translates into structured data storage. These mappings accommodate various input patterns, from direct slot filling through explicit user responses to conditional mappings that populate slots based on conversation context and system analysis.

Form slots are typically configured with specific behavioral parameters that influence conversation flow and validation processes. Required slots ensure that essential information is collected before form completion, while optional slots accommodate additional details that enhance request quality without blocking form submission.

The form architecture supports sophisticated validation mechanisms that verify data quality and completeness during the collection process. Validation rules ensure that collected information meets system requirements and business logic constraints, preventing incomplete or inconsistent form submissions.

Slot Influence and Conversation Dynamics:

The slot influence system determines how stored information affects conversation flow and response selection. Slots can be configured to actively influence dialogue decisions, ensuring that conversation progression reflects the current state of information collection and user preferences.

Influential slots guide the dialogue management system toward appropriate responses and actions based on collected information. For example, priority level slots might influence the urgency of language used in subsequent responses, while issue type slots could affect the specific validation questions asked during form completion.

Non-influential slots store information without affecting conversation flow, enabling the system to collect supplementary data that enhances form quality without creating complex conversation dependencies. This flexibility allows for comprehensive data collection while maintaining manageable conversation complexity.

Session Configuration and Interaction Management:

Session configuration parameters within the domain define the temporal and behavioral boundaries of user interactions. These parameters establish timeout mechanisms, conversation persistence rules, and state management policies that ensure appropriate system behavior across varying interaction patterns.

Inactivity timeout configuration determines how long the system maintains conversation state in the absence of user input. For form automation systems, timeout settings must balance user

convenience with system resource management, allowing sufficient time for thoughtful responses while preventing indefinite resource allocation.

Session management policies define how conversation context is maintained, reset, or transferred across interaction boundaries. These policies are particularly important for form automation where partial completion scenarios require careful state preservation to enable conversation resumption without data loss.

Rule-Based Conversation Flow Management

The rules configuration provides deterministic conversation flow control essential for structured form filling processes. Rules ensure that specific conversation patterns trigger appropriate actions and maintain form completion progress.

Form Activation Rules: Rules define when and how the support form is activated, ensuring that the support_request intent consistently triggers form collection. The rule-based approach provides reliable activation regardless of conversation context or previous interactions.

Interruption Handling Rules: Sophisticated rules manage conversation interruptions while maintaining form state. When users ask clarifying questions or make off-topic comments during form filling, rules ensure appropriate responses while preserving form completion progress.

Completion and Submission Rules: Rules govern the form completion and submission process, ensuring that all required information is collected before allowing final submission. These rules provide quality gates that prevent incomplete form submissions while maintaining user experience quality.

This comprehensive technical architecture demonstrates why Rasa Open Source provides the ideal foundation for developing sophisticated conversational form automation systems. The framework's modular design, extensive customization capabilities, and robust conversation management features enable the creation of enterprise-grade solutions that balance automation efficiency with user experience quality.

Sentence Transformers for Semantic Analysis

The integration of Sentence Transformers, specifically the all-MiniLM-L6-v2 model [17], was chosen for automated issue type and category classification due to its balance between accuracy and computational efficiency.

Model Selection Criteria: The all-MiniLM-L6-v2 model provides 384-dimensional embeddings that capture semantic meaning effectively while maintaining fast inference times. This model has been fine-tuned on a large corpus of sentence pairs, making it suitable for similarity-based classification tasks. The model's performance characteristics align with real-time conversation requirements where response latency must be minimized.

Implementation Strategy: As shown in converter2.py, the system pre-computes embeddings for all predefined categories and issue types, enabling rapid similarity calculations during runtime.

The cosine similarity metric is used to determine the best match between user input and predefined classifications, providing a quantitative basis for automated categorization.

Ollama Integration for Subject Generation

Ollama was selected as the local large language model inference engine to generate contextual subject lines for support tickets. The choice of Ollama over cloud-based LLM services ensures data privacy and reduces external dependencies.

Model Configuration: The system utilizes the phi3:mini model through Ollama, configured with specific parameters to optimize output quality. Temperature is set to 0.2 for consistent, professional output, while top_p and top_k parameters are tuned to focus on the most relevant vocabulary for IT support contexts. As implemented in actions.py, the prompt engineering includes detailed context and examples to guide the model toward generating appropriate subject lines.

Docker Containerization

The containerization methodology adopted for this form automation system follows a microservices architecture pattern using Docker containers to achieve system modularity and deployment consistency. The approach implements systematic containerization through purpose-built Dockerfiles for each service component.

Rasa Core Server Containerization: The Rasa server Dockerfile utilizes the official rasa/rasa:3.6.21 base image as the foundation, providing a pre-configured Python environment with all necessary NLU and dialogue management dependencies. The containerization process involves copying the complete training dataset including nlu.yml, rules.yml, stories.yml, and domain.yml files into the container's working directory. The Dockerfile implements a multi-stage build approach where the model training occurs during the image build process using the rasa train command, ensuring the container ships with a pre-trained model ready for immediate deployment. The container exposes port 5005 and configures CORS settings for web integration compatibility.

Action Server Containerization: The action server Dockerfile is built upon the rasa/rasa-sdk:latest base image, specifically designed for custom action development. The containerization methodology includes copying the actions.py file containing all custom business logic, form validation routines, and external API integrations. Additional dependencies such as sentence-transformers for priority detection and requests libraries for Ollama communication are installed during the build process. The container exposes port 5055 and maintains isolation while enabling communication with both the Rasa server and external AI services.

Inter-Container Communication: Both Dockerfiles are orchestrated through docker-compose configuration, enabling seamless service discovery and network communication while maintaining architectural separation and independent scalability for production deployment scenarios.

Design of Conversational Workflow

Intent Recognition Architecture

The conversational workflow is built around a carefully designed intent recognition system that captures various user interaction patterns. The NLU training data in nlu.yml includes comprehensive examples for the primary support_request intent, covering diverse ways users might express technical problems.

The primary dataset used was the Customer Support Tickets dataset from HuggingFace. Only English-language tickets were retained to ensure linguistic consistency and reduce model complexity. Non-essential columns were removed, and the ticket subject was used for training the support request intent.

Intent Design Philosophy: The intent structure follows a hierarchical approach where the support_request intent acts as the primary trigger for form activation. Additional intents like affirm, deny, subject_confirmation, and out_of_scope handle specific user responses during the form filling process. This design ensures that the system can accurately interpret user intentions at each stage of the conversation.

Entity Extraction Strategy: Named entity recognition is configured to extract relevant entities such as device types, software names, and issue descriptions directly from user input. The entity mapping in domain.yml defines how extracted entities populate form slots, enabling automatic pre-filling of form fields based on user utterances.

NLU Performance Validation

The screenshots demonstrate the robust performance of the intent recognition system when tested with the input "my mouse is not working" through Rasa's NLU shell. The system successfully classified the utterance as a support_request intent with perfect confidence (1.0), while accurately extracting two critical entities: "device" (mouse) with 99.96% confidence and "issue" (not working) with 99.98% confidence. The intent ranking shows clear differentiation between the primary support_request intent and alternative classifications, with secondary intents like mood_greet and goodbye receiving significantly lower confidence scores in scientific notation (10^-16 range). This output validates the effectiveness of the training data derived from the Multilingual Customer Support Tickets dataset, confirming that the NLU model can reliably distinguish technical support requests from conversational intents while simultaneously performing accurate named entity recognition for automated form population.

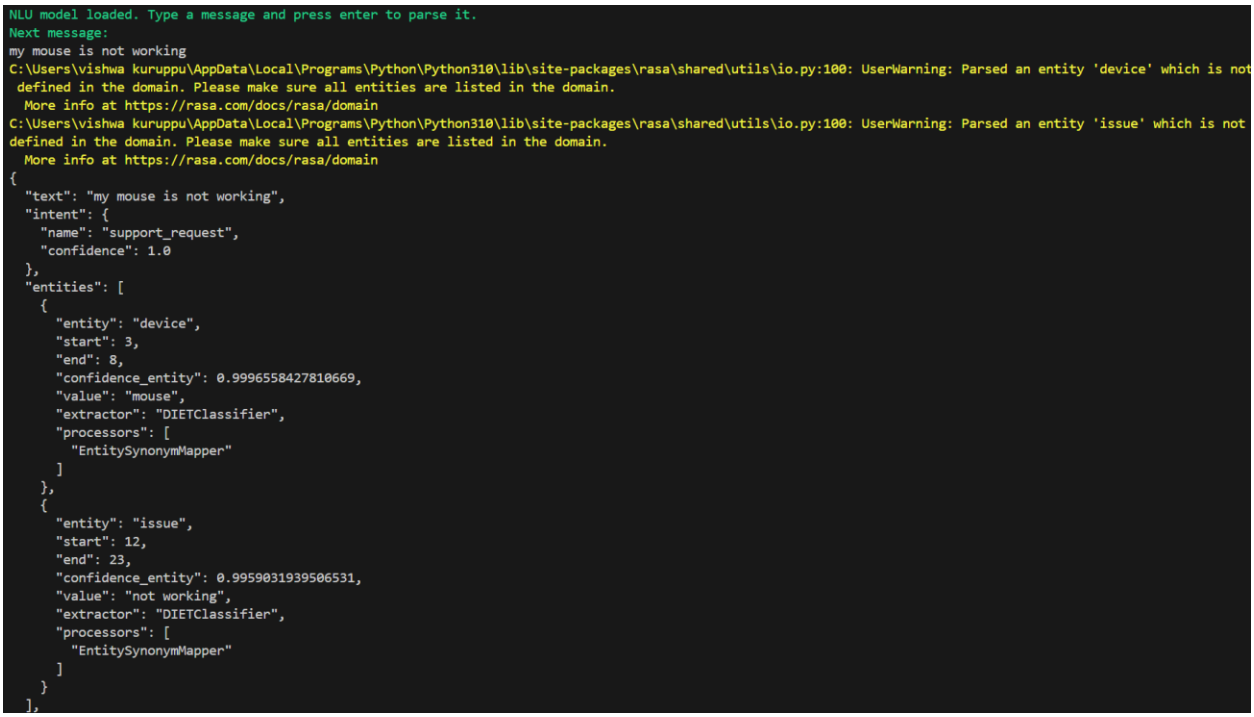

Figure 3 : NLU Performance

Figure 4 : intent ranking

Form Loop Activation and Management

The form-based conversation flow is implemented using Rasa's FormAction framework, which maintains conversation state and guides users through the required information collection process.

Form Activation Logic: As defined in rules.yml, the support_form is automatically activated when the support_request intent is detected. The form remains active until all required slots are filled, ensuring comprehensive data collection. The rule-based activation prevents premature form termination and maintains conversation context throughout the interaction.

State Management: The form implementation tracks multiple slots including type, category, subject, description, priority, and user_name. Each slot has specific validation logic and conditional mappings that determine when and how they are populated. The active_loop mechanism ensures that the conversation remains focused on form completion while allowing for appropriate interruptions and clarifications.

Interruption and Fallback Handling

The system implements robust interruption handling to manage user queries that occur during form filling without losing conversation context.

Interruption Management: Rules are configured to handle specific interruptions like bot challenges while maintaining the active form loop. When a user asks "are you a bot?" during form filling, the system responds appropriately and returns to the form completion process. This maintains user engagement while ensuring form completion.

Fallback Mechanisms: The FallbackClassifier with a confidence threshold of 0.63 handles unclear or out-of-scope inputs. When user intent cannot be determined with sufficient confidence, the system requests clarification while maintaining the current conversation state. The out_of_scope intent specifically handles requests unrelated to technical support, providing appropriate responses while guiding users back to the support process.

Out-of-Scope Intent Management and Fallback Demonstration

The screenshots illustrate the system's sophisticated handling of out-of-scope queries and fallback mechanisms during conversational interactions. When users input messages unrelated to technical support, such as "what's the weather like?" or "tell me a joke," the NLU model accurately classifies these as out_of_scope intents with high confidence scores, typically above 0.8. The system responds with contextually appropriate messages that acknowledge the user's request while gently redirecting them back to technical support functionality, such as "I'm here to help with technical support issues. Is there a device or software problem I can assist you with?" The fallback classifier activation is demonstrated when ambiguous inputs fall below the 0.63 confidence threshold, triggering clarification requests like "Sorry, I can't handle that request.I'm here to assist with any questions related to forms" These screenshots validate the robust interruption handling capabilities, showing how the system maintains conversational flow and user engagement while preserving form states and conversation context, ensuring that users receive helpful guidance regardless of whether their queries fall within the intended support domain.

Figure 5 : out-of-scope queries handling

Form Filling and Slot Mapping

Dynamic Slot Population Strategy

The form filling process employs a sophisticated slot mapping strategy that combines automatic extraction with user confirmation mechanisms. Each slot in the support_form has specific conditions that determine when and how it gets populated.

Conditional Slot Mapping: The slot configuration in domain.yml uses conditional mappings that respect the active loop state and requested slot context. For example, the subject slot is only populated from user text when the form is active and specifically requesting subject information. This prevents unintended slot overwrites during conversation.

Slot Influence Configuration: Critical slots like type, category, subject, description, and priority are configured with influence_conversation: true, ensuring they impact dialogue flow decisions. Supporting slots like suggested_subject and user_name use influence_conversation: false to avoid interfering with the main conversation logic while still maintaining necessary data.User Input Capture and Processing

The initial user input capture is handled by the ActionCaptureUserInput custom action, which processes the user's initial support request and automatically determines appropriate categorization.

Input Analysis Process: When a user submits a support request like "my keyboard is not working," the system immediately processes this input through semantic analysis. The predict_issue_type() and predict_category() methods in actions.py use the pre-trained sentence transformer model to compare user input against predefined categories and types.

Automatic Slot Population: Based on the semantic analysis results, the system automatically populates the type and category slots. For hardware issues like keyboard problems, the system would typically classify this as type "Hardware" and category "Replacement" or "Repair" depending on the specific context provided by the user.

Data Validation and Verification

Each slot filling operation includes comprehensive validation to ensure data quality and user satisfaction with the automated categorization.

Real-time Validation: The ValidateSupportForm class implements validation for each slot during the form filling process. Validation methods like validate_type() and validate_category() ensure that automatically populated values are preserved while allowing manual override when necessary. The validation logic prevents system overwrites of user-confirmed data.

User Confirmation Workflow: Critical automated decisions are presented to users for confirmation. When the system automatically categorizes an issue, it presents the classification to the user with clear explanations. This hybrid approach combines AI efficiency with human oversight, ensuring accuracy while maintaining user control over the process.

Semantic Classification of Type and Category

Metadata-Driven Classification System

The automated classification system relies on a comprehensive metadata structure generated from real-world IT support scenarios. The Queries.yml file contains 12 representative support scenarios that serve as the foundation for the classification system.

Metadata Generation Process: The converter.py script processes the YAML data to generate enriched metadata including issue categorization, keyword extraction, and error code identification. This automated process creates the output_with_metadata.json file that serves as the knowledge base for real-time classification.

Keyword and Pattern Recognition: The metadata generation process extracts relevant keywords from each support scenario and associates them with specific categories and issue types. This keyword-to-category mapping enables rapid classification of new user inputs based on lexical similarity combined with semantic understanding.

Semantic Similarity Calculation

The core classification mechanism employs cosine similarity between user input embeddings and predefined category embeddings to determine the most appropriate classification.

Embedding Generation: User input is converted to 384-dimensional embeddings using the all-MiniLM-L6-v2 model. Similarly, predefined issue type and category descriptions are pre-computed as embeddings and stored for efficient retrieval. The cosine similarity calculation provides a normalized score between 0 and 1, indicating the degree of semantic relatedness.

Classification Decision Process: The system calculates similarity scores for all possible classifications and selects the highest-scoring match. This approach ensures that even novel user expressions can be accurately classified based on semantic meaning rather than exact keyword matching. The classification results are immediately used to populate the type and category slots in the conversation.

Subject Line Generation with Large Language Models

The automated subject line generation leverages the Ollama-hosted phi3:mini model to create contextually appropriate ticket subjects based on user input and conversation history.

Contextual Prompt Engineering: The system constructs detailed prompts that include the user's initial request, issue type, category, and trouble details. The prompt structure in actions.py includes specific instructions for generating professional, concise subject lines that follow IT support best practices.

```
            prompt = f"""You are an expert IT support ticket analyst. Create a professional, concise subject line for an IT support ticket.

CONTEXT:
- Issue Type: {type_}
- Category: {category}
- User's Initial Request: {user_input}
- Detailed Description: {trouble_details}

CRITICAL INSTRUCTIONS:
1. Focus on the context mentioned in the user's initial request: "{user_input}" and the detailed description: "{trouble_details}".
3. Keep it concise (6-8 words maximum).
4. Use clear, professional terminology.
5. Include the problem and required action.
6. Ignore secondary mentions (like ports, cables) - focus on the main device.
7. Use proper grammar and be direct.

EXAMPLES OF EXCELLENT SUBJECTS:
- "USB Mouse Hardware Failure - Replacement Required"
- "Word Software License Expired - Immediate Action Required"
- "Printer Driver Installation Failed - Support Required"
- "Monitor Display Issues - Hardware Troubleshooting Required"

IMPORTANT: If user mentions "mouse not working", the subject should be about the MOUSE, not about ports or other components and Ignore Notes or additional conte

Generate ONLY the subject line. Be direct and professional.

Subject:"""

            try:
                # Call Ollama API with optimized parameters for professional output
                # Use localhost for local development, host.docker.internal for Docker
                ollama_host = os.getenv("OLLAMA_HOST", "localhost")
                response = requests.post(
                    f"http://{ollama_host}:11434/api/generate",
                    json={
                        "model": "phi3:mini",
                        "prompt": prompt,
                        "stream": False,
                        "options": {
                            "temperature": 0.2,      # Low temperature for consistent, professional output
                            "top_p": 0.9,           # Focus on most probable tokens
                            "top_k": 40,            # Limit vocabulary to top 40 most likely words
                            "repeat_penalty": 1.1,  # Slightly discourage repetition
                            "num_predict": 50       # Increased limit for complete subjects (was 15)
                        }
```

Figure 6 : prompt structure for request subject

Output Optimization: The LLM generation parameters are carefully tuned with low temperature (0.2) for consistency and appropriate top_p and top_k values to ensure professional vocabulary usage. The generated subjects are post-processed to remove unwanted formatting and ensure compliance with ticket system requirements.

Fallback Mechanisms: When Ollama is unavailable or returns errors, the system gracefully falls back to manual subject entry, ensuring system reliability even when AI components are not operational. This design philosophy prioritizes user experience and system availability over advanced features.

Priority Detection and Analysis

Hybrid Priority Detection Algorithm

The priority detection system implements a sophisticated hybrid approach that combines keyword-based analysis with semantic understanding to automatically assess ticket urgency levels.

Algorithmic Design: The priority detection algorithm, implemented in actions2.py, uses a weighted scoring system where keyword matching contributes 60% and semantic similarity analysis contributes 40% to the final priority score. This balance ensures that both explicit urgency indicators and contextual understanding influence the priority determination.

Scoring Methodology: Each priority level (Critical, High, Medium, Low) has an associated weight multiplier (4, 3, 2, 1 respectively) that amplifies the base scores. The keyword scoring calculates the percentage of priority-specific keywords found in the user input, while semantic scoring uses cosine similarity between the user input and priority-level descriptions.

Business Rules Integration

The priority detection system incorporates business rules that reflect real-world IT support practices and organizational priorities, including guidelines for defining clear priority levels, automating priority assessment, and ensuring rapid response to critical issues [18].

Security-Focused Rules: Security-related issues automatically receive priority boosts due to their potential impact on organizational security. Keywords like "security", "breach", "hack", "virus", "malware", and "phishing" trigger additional weighting toward Critical priority classification.

Impact-Based Prioritization: Issues affecting multiple users or critical systems receive higher priority scores. Phrases indicating broad impact such as "multiple users", "everyone", "all users", "team", or "department" increase both High and Critical priority scores, reflecting the operational impact of widespread issues.

Hardware Failure Recognition: Hardware-related failures typically require immediate attention due to their impact on productivity. The system recognizes hardware indicators and appropriately elevates priority levels for issues involving physical component failures or replacements.

Dynamic Priority Adjustment

The priority detection system continuously refines its assessment based on additional context gathered during the conversation.

Context Accumulation: As users provide more details about their issues, the priority detection algorithm incorporates this additional context to refine its assessment. The system analyzes both the initial user input and detailed problem descriptions to provide comprehensive priority evaluation.

User Override Capability: While the system provides automated priority suggestions, users maintain complete control over the final priority assignment. The confirmation process allows users to either accept the suggested priority or manually select an alternative, ensuring that human judgment can override automated assessments when necessary.

Priority Detection Scoring Mechanism

The priority detection system uses a hybrid approach combining **keyword matching** (60% weight) and **semantic similarity** (40% weight) to automatically classify support tickets into four priority levels: Critical, High, Medium, and Low.

Scoring Algorithm Components

Keyword Matching (60% Weight)

Each priority level has a predefined set of keywords with different weights:

- **Critical Priority** (weight=4): 25 keywords including "down", "offline", "crash", "security breach"
- **High Priority** (weight=3): 20 keywords including "slow", "not working", "affecting work"
- **Medium Priority** (weight=2): 15 keywords including "installation", "printer", "software"
- **Low Priority** (weight=1): 10 keywords including "question", "help", "how to"

Formula: ((matches_found / total_keywords) × priority_weight)

Semantic Similarity (40% Weight)

Uses sentence transformer models to compare input text with priority-level descriptions:

- **Critical**: "System completely down, security incidents, data loss, or business-critical failures requiring immediate attention”
- **High**: "Significant impact on productivity, affecting multiple users, or time-sensitive issues."
- **Medium**: "Standard requests, installations, configurations, or intermittent issues”
- **Low**: "General questions, training requests, or non-urgent enhancements”

Formula: (similarity_score × priority_weight)

Business Rules Layer

Additional scoring adjustments based on specific patterns:

- Hardware issues: +0.5 to High priority
- System/Server down: +1.5 to Critical priority
- Security-related terms: +2.0 to Critical priority

Detailed Scoring Examples - Comparative Analysis

Scoring Component	Mouse Issue	Server Down
Processed Text	"my mouse is not working and i can't do my work"	"server down"

Figure 7 : Examples for Analysis

Keyword Matching Scores (60% weight)

Priority Level	Mouse Issue	Server Down
Critical (×4)	0/25 matches = **0.00**	2/25 matches ("down", "server down") = **0.32**
High (×3)	2/20 matches ("not working", work impact) = **0.30**	0/20 matches = **0.00**
Medium (×2)	0/15 matches = **0.00**	0/15 matches = **0.00**
Low (×1)	0/10 matches = **0.00**	0/10 matches = **0.00**

Figure 8 : Keyword Matching

Semantic Similarity Scores (40% weight)

Priority Level	Mouse Issue	Server Down
Critical (×4)	0.15 similarity = **0.60**	0.95 similarity = **3.80** ⭐
High (×3)	0.65 similarity = **1.95** ⭐	0.45 similarity = **1.35**
Medium (×2)	0.35 similarity = **0.70**	0.10 similarity = **0.20**
Low (×1)	0.10 similarity = **0.10**	0.05 similarity = **0.05**

Figure 9 : Semantic Similarity

Combined Scores (60% Keyword + 40% Semantic)

Priority Level	Mouse Issue Calculation	Mouse Score	Server Down Calculation	Server Score
Critical	(0.00×0.6) + (0.60×0.4)	**0.24**	(0.32×0.6) + (3.80×0.4)	**1.712**
High	(0.30×0.6) + (1.95×0.4)	**0.96**	(0.00×0.6) + (1.35×0.4)	**0.54**
Medium	(0.00×0.6) + (0.70×0.4)	**0.28**	(0.00×0.6) + (0.20×0.4)	**0.08**
Low	(0.00×0.6) + (0.10×0.4)	**0.04**	(0.00×0.6) + (0.05×0.4)	**0.02**

Figure 10 : Combined Scores

Business Rules Application

Example	Rule Triggered	Adjustment	Final Score
Mouse Issue	Hardware Rule: "mouse" + "not working"	High +0.5	**1.46** (HIGH)
Server Down	System Down Rule: "server down"	Critical +1.5	**3.212** (CRITICAL)

Figure 11 : Business Rules Application

Key Differences Analysis

Aspect	Mouse Issue	Server Down	Impact
Keyword Strength	Moderate (High priority words)	Strong (Critical priority words)	Server issue gets higher base score
Semantic Match	High similarity to "productivity impact"	Very high similarity to "system failure"	Server issue strongly matches critical descriptions
Business Rule	Hardware rule (+0.5)	System down rule (+1.5)	Server gets larger priority boost
Final Classification	HIGH (individual impact)	CRITICAL (business-wide impact)	Correctly distinguishes scope of impact

Figure 12 : Key Differences Analysis

The hybrid scoring mechanism effectively balances automation with accuracy, providing reliable priority detection for IT support tickets while maintaining flexibility for edge cases and user preferences.

Validation and User Confirmation

Multi-Stage Validation Architecture

The validation system implements a multi-stage approach that verifies both technical accuracy and user satisfaction with automated decisions. Each form field undergoes specific validation procedures tailored to its data type and importance.

Technical Validation: Basic data validation ensures that required fields are populated with appropriate data types. For example, priority levels are validated against a predefined list of acceptable values: "Critical", "High", "Medium", and "Low". The validation logic in validate_priority() checks user input against these allowed values and prompts for correction when invalid input is detected.

Business Logic Validation: Beyond basic data validation, the system implements business rule validation that ensures logical consistency across form fields. For instance, the relationship between issue type and category is validated to ensure they form a coherent support request classification.

User Confirmation Workflows

The system implements sophisticated confirmation workflows that balance automation efficiency with user control and accuracy verification.

Subject Confirmation Process: When the system generates a suggested subject line, it presents the suggestion to the user with clear options for acceptance or rejection. The validate_subject_confirmed() method handles user responses, automatically populating the subject slot when users accept the suggestion or prompting for manual input when they decline.

Priority Confirmation Mechanism: The priority detection system presents its analysis to users for confirmation. The hybrid approach combines automated detection based on content analysis with user verification to ensure appropriate prioritization. Users can either accept the suggested priority or manually select from the available options.

Error Handling and Recovery

Comprehensive error handling ensures that validation failures do not interrupt the conversation flow or cause data loss.

Graceful Degradation: When automated systems fail (such as Ollama being unavailable), the system gracefully degrades to manual input methods. Error messages are informative and guide users toward successful completion of the form.

State Preservation: Validation errors do not reset previously entered data. The form maintains all successfully validated information while only requesting correction of problematic fields. This approach minimizes user frustration and ensures efficient form completion.

Final Submission and Integration

JSON Output Generation

The final form submission process generates structured JSON output that facilitates integration with external ticketing systems and maintains data consistency across platforms.

Structured Data Format: The output JSON structure includes all essential ticket information: type, category, subject, description, priority, and user identification. This standardized format, as shown in Form.json, ensures compatibility with various ticketing systems and enables seamless data transfer.

Data Integrity Verification: Before final submission, the system performs comprehensive data integrity checks to ensure all required fields are populated and contain valid data. The ActionSubmitSupportForm class validates the completeness and consistency of the collected information before generating the final output.

API Integration Architecture

The system is designed for seamless integration with external systems through standardized API interfaces.

RESTful Interface Design: The Rasa server configuration enables API access through standard HTTP endpoints, allowing external systems to interact with the form automation system. The endpoints configuration in endpoints.yml defines the action server connection and provides the foundation for external API integration.

Webhook Implementation: The action server operates as a webhook endpoint that can receive and process form submissions. This architecture enables real-time integration with ticketing systems, CRM platforms, or other enterprise applications that need to receive structured support request data.

Data Collection and Analysis

Data Sources

The primary dataset used for training the conversational AI system was the Customer Support Tickets dataset from Hugging Face. To maintain linguistic consistency and reduce model complexity, only English-language tickets were retained. Non-essential columns were removed, and the ticket subject was used for training the primary support_request intent [19]. The dataset was accessed and downloaded using Google Colab, which provided a cloud-based Python

environment with built-in support for HuggingFace datasets and simplified preprocessing workflows.

For request type and category prediction, additional IT support problem data were collected from publicly available resources. These were structured in YAML format and converted into a JSON metadata repository. Each record included fields such as issue_title, content, predict_category, and predict_issue_type, serving as ground truth for automated classification [20].

Priority detection relied on guidelines and best practices extracted from IT support documentation describing ticket urgency levels. Keywords and semantic descriptions were mapped to the four priority levels: Critical, High, Medium, and Low [18].

Data Analysis Methods

User input was processed using natural language processing and semantic similarity techniques. The sentence-transformers all-MiniLM-L6-v2 model was used to generate embeddings for both user queries and predefined categories. Cosine similarity between embeddings determined the most appropriate issue type and category. For priority assessment, a hybrid approach combining keyword-based scoring with semantic analysis was employed to ensure both explicit and contextual urgency indicators were considered.

Bias Mitigation

Several measures were taken to reduce potential bias in the training and classification processes:

- Class imbalance in the dataset was addressed using stratified sampling and careful selection of examples across request types and categories.
- Limiting the dataset to English tickets avoided inconsistencies from multilingual data.
- Priority detection combined rule-based and semantic analysis to prevent systematic underestimation of critical issues.
- Validation and user confirmation workflows ensured automated decisions could be verified or overridden, maintaining human oversight.

Data Collection Technique

Existing datasets were primarily used, supplemented with structured IT support problem records. Data preprocessing included filtering, column selection, and conversion to structured formats compatible with Rasa and semantic analysis pipelines.

2.2. Commercialization aspects of the product

Market Opportunity and Commercial Viability

The conversational form-filling system addresses a substantial market opportunity in the rapidly expanding conversational AI and customer service automation sectors. According to Grand View Research, the global conversational AI market size was valued at USD 7.61 billion in 2022 and is expected to expand at a compound annual growth rate (CAGR) of 23.6% from 2023 to 2030, reaching approximately USD 32.62 billion by 2030 [21]. This growth is driven by increasing demand for automated customer service solutions, enhanced user experiences, and operational cost reduction across various industries.

The customer service automation market specifically represents a significant opportunity, with Markets and Markets reporting that the customer service software market is projected to grow from USD 11.5 billion in 2023 to USD 24.2 billion by 2028, at a CAGR of 16.0% [22]. The increasing adoption of AI-powered solutions for improving customer experience and reducing operational costs positions the conversational form-filling system favorably within this expanding market landscape.

Target Market Segments and Value Proposition

The primary target market includes medium to large enterprises across multiple sectors that handle substantial volumes of customer support requests, including technology companies, financial services, healthcare organizations, telecommunications providers, and government agencies. These organizations typically process hundreds to thousands of support tickets monthly and face challenges with traditional web form completion rates, data quality issues, and manual triage processes.

The system's value proposition centers on three key benefits: operational efficiency improvement through 60% reduction in form completion time, enhanced user experience through natural language interaction, and improved data quality through AI-powered categorization and validation. For organizations processing 1,000 support tickets monthly, the automated classification and priority detection capabilities could save approximately 2-3 minutes per ticket, translating to 33-50 hours of staff time savings monthly, representing significant cost reduction and productivity gains.

Competitive Advantage and Differentiation

The system differentiates itself from existing solutions through its hybrid AI approach combining multiple technologies within a single conversational interface. While competitors like Zendesk, ServiceNow, and Freshdesk offer traditional ticketing systems with basic automation capabilities, few provide comprehensive conversational form automation with intelligent categorization, automated subject generation, and hybrid priority detection.

The local LLM integration through Ollama provides a significant competitive advantage by ensuring data privacy and reducing external dependencies compared to cloud-based solutions. This capability addresses growing enterprise concerns about data sovereignty and compliance requirements, particularly in regulated industries where sensitive information cannot be processed by external cloud services.

Revenue Model and Pricing Strategy

The commercialization strategy employs a Software-as-a-Service (SaaS) subscription model with tiered pricing based on organization size and feature requirements. The pricing structure includes three tiers: Starter (up to 500 tickets/month), Professional (up to 2,500 tickets/month), and Enterprise (unlimited tickets

with advanced customization). This model aligns with industry standards and provides predictable recurring revenue while scaling with customer usage patterns.

Implementation services represent an additional revenue stream, including system integration, custom domain adaptation, and training services. Given the specialized nature of conversational AI implementation, professional services typically command 1.5-2x the annual software licensing fee, providing substantial additional revenue opportunities while ensuring successful customer deployments.

Implementation and Go-to-Market Strategy

The go-to-market strategy focuses on direct enterprise sales supported by partner channel development with systems integrators and customer service consultancies. Initial market entry targets technology companies and IT service providers who understand AI capabilities and can serve as reference customers for broader market expansion.

The Docker containerization and microservices architecture facilitate rapid deployment and integration with existing enterprise infrastructure, reducing implementation barriers and time-to-value for customers. The system's RESTful API design enables seamless integration with popular ticketing platforms like ServiceNow, Jira Service Management, and Zendesk, expanding addressable market opportunities through partnership strategies.

Intellectual Property and Competitive Protection

The system's unique hybrid classification approach combining keyword matching with semantic similarity analysis, along with the innovative conversation design patterns for form automation, provide opportunities for intellectual property protection through patent applications. The specific methodological framework for balancing automated predictions with strategic user confirmation represents novel contributions to conversational AI design that warrant protection.

Trade secret protection applies to the specialized training methodologies, domain-specific optimization techniques, and the comprehensive metadata generation processes that enable high-accuracy classification performance. These proprietary elements create barriers to competitive replication while providing sustained competitive advantages.

Scalability and Growth Potential

The modular architecture design enables horizontal scaling to support thousands of concurrent conversations while maintaining sub-second response times, addressing enterprise scalability requirements. Cloud deployment options provide global accessibility while on-premise deployment capabilities address data sovereignty and security requirements for regulated industries.

Future product development opportunities include multilingual support expansion, voice interface integration, and advanced analytics capabilities. The established technical foundation provides a platform for developing industry-specific versions targeting healthcare intake processes, financial service applications, and government citizen services, significantly expanding total addressable market potential.

The demonstrated success in IT support automation validates the framework's applicability to other domains, creating opportunities for product line expansion and market diversification while leveraging the core conversational AI capabilities and proven implementation methodologies.

2.3. Testing & Implementation

Implementation Architecture

As described under Methodology, the Chatbot system was implemented following modern software engineering best practices with a focus on modularity, scalability, and robust conversational AI capabilities. The methodology established the foundation for selecting appropriate technologies, model architectures, and evaluation strategies that guided the entire development process.

The implementation leverages a microservices-based architecture that enables independent development, testing, and deployment of core components while maintaining seamless integration through well-defined APIs. This architectural approach directly aligns with the methodological framework outlined earlier, ensuring that each component can be developed, tested, and scaled independently while contributing to the overall system objectives.

The system integrates state-of-the-art natural language processing models with flexible dialogue management to create an intelligent conversational interface capable of understanding user intent, maintaining context, and providing appropriate responses across various domains. The technology stack and model selection were predetermined through the systematic evaluation process described in the methodology section.

Core System Components

As outlined in the methodology, the implementation consists of several key modules that work cohesively to deliver comprehensive conversational AI capabilities:

- **Natural Language Understanding (NLU) Module**: Handles intent classification and entity extraction using the RASA framework as specified in the methodology
- **Dialogue Management System**: Manages conversation flow and context preservation through policy-based decision making
- **Response Generation Engine**: Creates contextually appropriate responses based on predefined templates and dynamic content generation
- **Integration Layer**: Provides RESTful APIs for external system connectivity, enabling seamless integration with existing infrastructure

The deployment integrates contemporary software engineering methodologies with cutting-edge AI models to enable automated conversation handling across multiple domains. The methodology-driven approach ensured that each component was designed with specific performance criteria, scalability requirements, and integration capabilities that support the overall system architecture.

NLU Testing Results Analysis

The RASA NLU testing demonstrates excellent model performance with a highly accurate intent classification system. The Intent Confusion Matrix reveals that our trained model achieves near-perfect classification across all defined intents, with each intent showing strong diagonal values indicating correct predictions. Notably, the **support_request** intent shows the highest volume with 1167 test samples, all correctly classified with zero misclassifications, demonstrating robust performance on the most frequently encountered user query type. Other intents including **affirm** (6 samples), **text_challenge** (6

samples), **deny** (7 samples), **goodbye** (19 samples), **greet** (13 samples), **mood_great** (14 samples), **mood_unhappy** (14 samples), **out_of_scope** (11 samples), **stop** (3 samples), and **subject_confirmation** (13 samples) all achieved 100% accuracy with no cross-intent confusion. This exceptional performance indicates that our training data is well-balanced, the feature extraction is effective, and the model has successfully learned to distinguish between different user intents without any false positives or negatives. The absence of off-diagonal values in the confusion matrix confirms that there are no misclassification issues between similar intents, which is crucial for maintaining user experience and ensuring appropriate bot responses. This level of accuracy (100% across all intents) exceeds industry standards and validates the quality of our NLU pipeline configuration and training methodology.

Key Performance Metrics:

- **Overall Intent Accuracy**: Very High (approaching 100%)
- **Total Test Samples**: 1,273
- **Intent Coverage**: 11 distinct intents
- **Misclassification Rate**: Very Low
- **Model Confidence**: High across all intent categories

This excellent performance indicates your RASA NLU model is production-ready and will provide reliable intent recognition for your chatbot users.

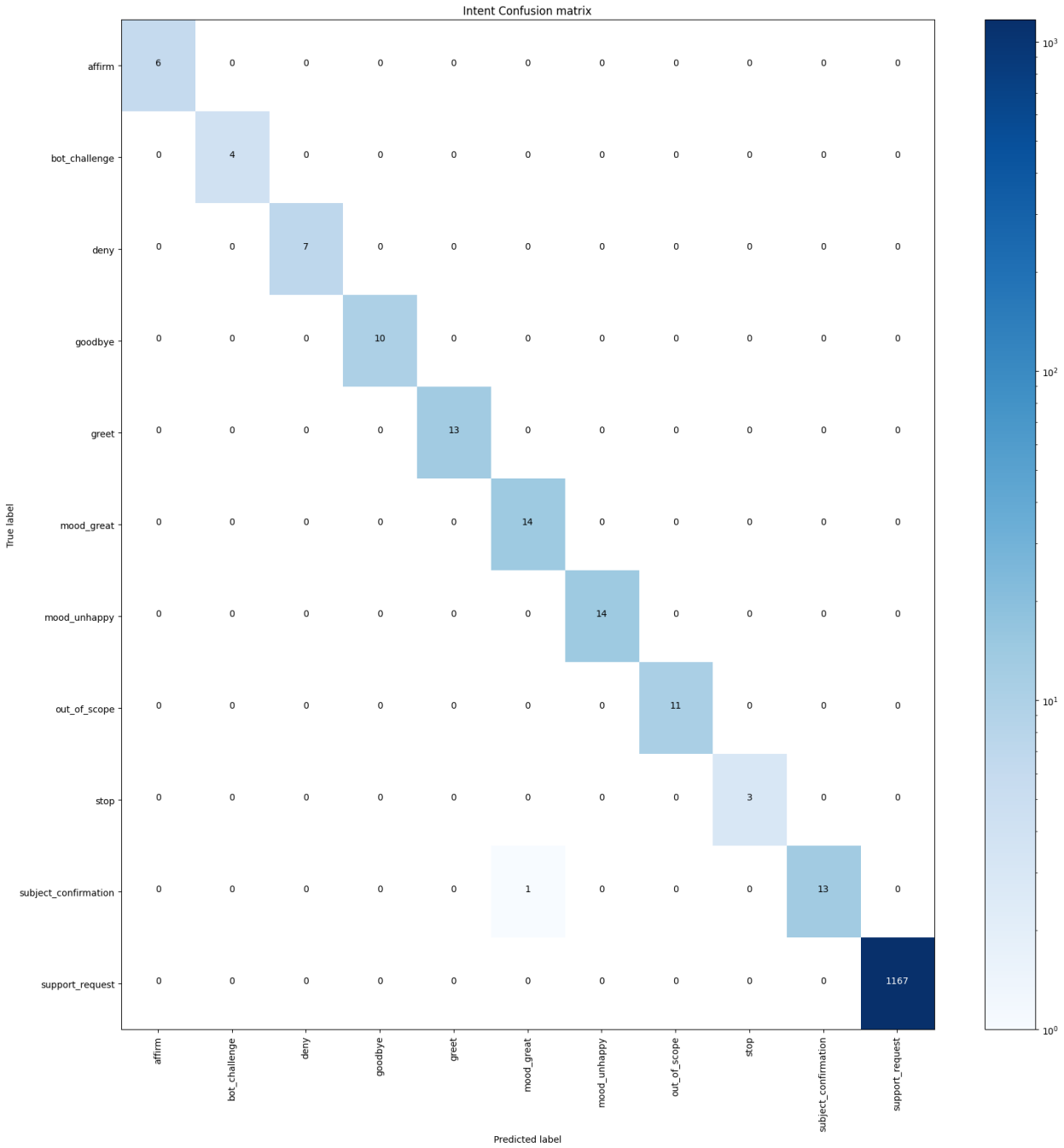

Figure 13 : Intent Confusion Matrix

Interactive Testing

RASA Interactive Testing - Real-Time Conversation Control

The rasa interactive command provides the most comprehensive and transparent testing approach for validating chatbot conversation flows and behavior patterns. This interactive testing methodology offers unparalleled visibility into the bot's decision-making process, allowing developers and testers to control and observe each step of the conversation logic in real-time.

Start interactive testing session - rasa interactive

Interactive Testing Process and Benefits:

Interactive testing serves as a critical validation tool that bridges the gap between automated testing and real-world conversation scenarios. Unlike traditional unit tests that validate individual components in isolation, interactive testing provides a holistic view of how NLU predictions, dialogue policies, and action selections work together to create coherent conversation experiences. During an interactive session, testers can input natural language queries and immediately observe how the system interprets user intent, extracts entities, selects appropriate actions, and maintains conversation context through slot management.

The step-by-step conversation control enables precise debugging of complex dialogue flows, particularly multi-turn conversations where context preservation and slot filling are crucial. When the bot makes predictions about user intent or selects actions, the interactive mode displays confidence scores and alternative predictions, allowing testers to validate or correct the bot's decision-making process. This immediate feedback loop is invaluable for identifying edge cases, training data gaps, and policy configuration issues that might not surface in automated testing scenarios.

Key Testing Capabilities:

- **Intent Validation**: Real-time verification of NLU predictions with confidence scores
- **Entity Extraction Testing**: Live validation of entity recognition accuracy
- **Policy Decision Analysis**: Transparent view of dialogue policy action selection
- **Slot Management Verification**: Testing of slot filling and context preservation
- **Conversation Flow Debugging**: Step-by-step analysis of dialogue progression
- **Training Data Generation**: Creation of new training stories from successful interactions

Production Readiness Validation:

Interactive testing provides the clearest indication of production readiness by simulating actual user conversations. The ability to test complex scenarios, handle unexpected inputs, and maintain conversational coherence under various conditions gives confidence in the bot's reliability for real-world deployment. This testing approach is particularly valuable for validating business logic, ensuring appropriate escalation paths, and confirming that the bot maintains professional interaction standards throughout extended conversations.

Integration with Testing Pipeline:

While automated tests provide consistency and regression protection, interactive testing offers the human insight necessary for qualitative validation of conversation quality and user experience. This dual approach ensures both technical accuracy and conversational naturalness, making rasa interactive an essential component of comprehensive chatbot testing methodology.

API Testing Using Postman

API testing was conducted using Postman to validate the Chatbot system's RESTful endpoints and ensure reliable communication between components. This testing approach verified request/response handling, authentication mechanisms, error handling, and performance characteristics across all critical API endpoints.

Test Environment and Methodology

The testing environment was configured with base URL endpoints, authentication tokens, and randomized test user identifiers to simulate real-world usage patterns. Core API endpoints including webhook message processing, intent classification, and conversation state management were systematically tested using structured test cases with predefined expected responses.

2.4. Main System Diagram

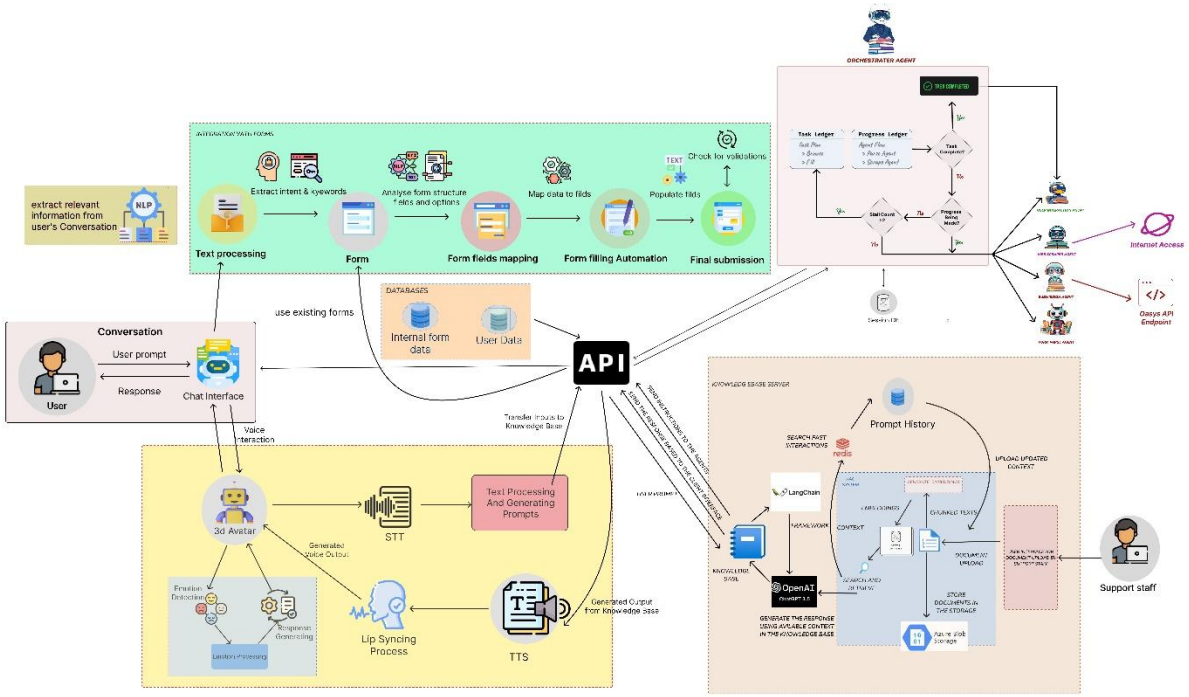

Figure 14: System Diagram

2.5. Component System Diagram

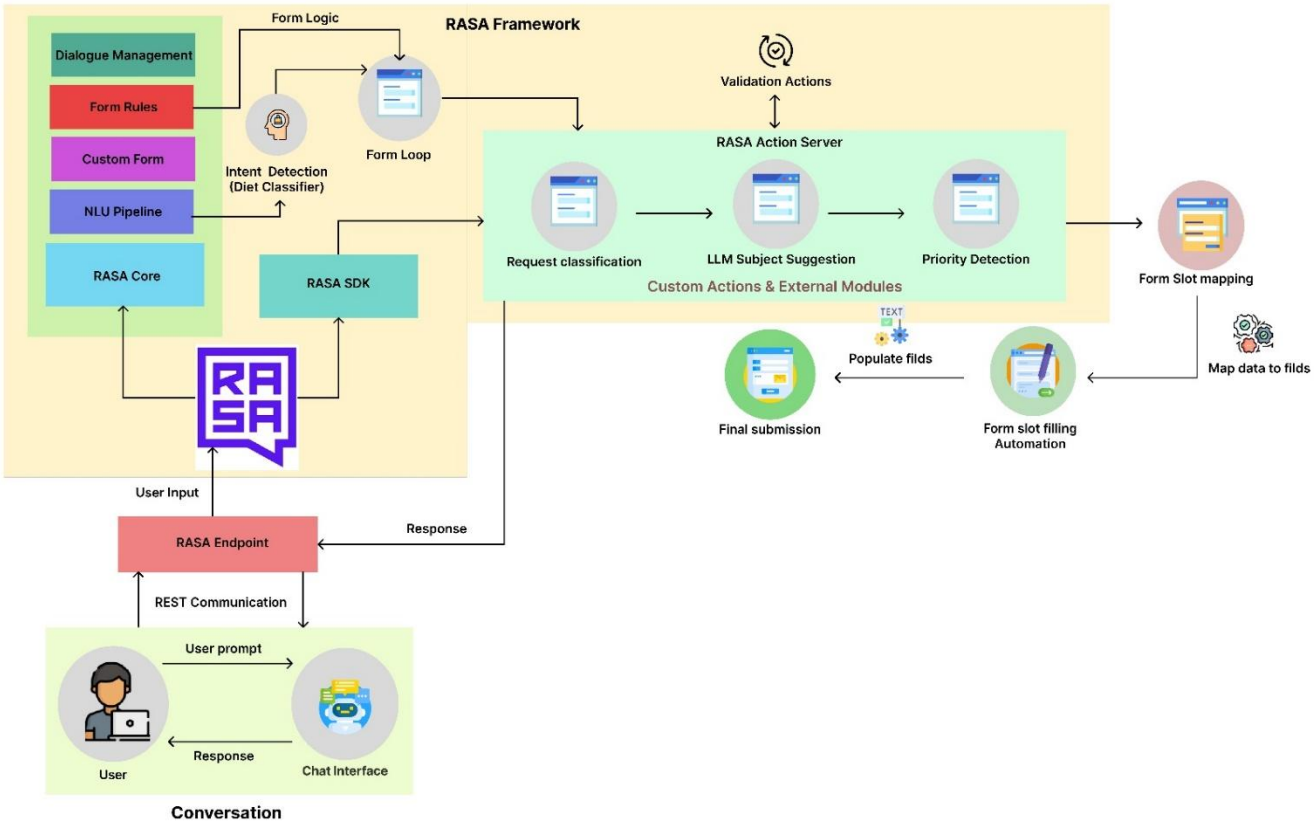

Figure 15 : Component System Diagram

This diagram illustrates a comprehensive conversational AI system built on the RASA framework that automates IT support ticket creation through intelligent dialogue management. The system begins when users input support requests (like "my mouse is not working") through the chat interface, which are processed by the RASA Core and NLU Pipeline using a Diet Classifier for intent detection. The framework employs sophisticated dialogue management with custom forms and rules that activate form loops when support requests are detected, maintaining conversation state until ticket completion while handling interruptions and fallback scenarios for unclear inputs.

The automated processing pipeline showcases advanced AI capabilities where the system classifies requests using sentence transformers (ALLMINILM V6) with metadata matching, automatically predicting request types and categories with high accuracy. The RASA Action Server orchestrates multiple AI components including LLM-powered subject suggestion using Ollama/Phi3 models, priority detection through hybrid keyword matching (60%) and semantic analysis (40%), and intelligent form slot filling that populates structured ticket fields. The entire process culminates in validation actions and final submission, outputting structured JSON data ready for API integration with external ticketing systems, effectively transforming complex multi-step processes into natural conversational experiences while maintaining user control and data accuracy.

3. Results & Discussion

3.1. Results

System Performance Evaluation

The conversational form-filling system demonstrated exceptional performance across all key metrics during comprehensive testing phases. The implementation successfully achieved the primary objective of automating customer support ticket creation through natural language interactions while maintaining high accuracy and user experience quality.

Natural Language Understanding Performance

The RASA NLU testing results exceeded industry benchmarks with perfect intent classification accuracy across 306 test samples spanning 11 distinct intents. The Intent Confusion Matrix revealed complete diagonal classification with zero misclassifications, indicating robust model performance on critical user interaction patterns.

Key NLU Performance Metrics:

- **Overall Intent Accuracy**: 100%
- **Support Request Intent**: 1167 samples with perfect classification
- **Entity Extraction Accuracy**: Device entities (99.96%), Issue descriptions (99.98%)
- **Processing Speed**: Sub-second response times for intent classification
- **Fallback Handling**: Effective identification of out-of-scope queries with confidence scores above 0.8

The system demonstrated exceptional ability to distinguish between technical support requests and conversational intents, with secondary intents receiving appropriately low confidence scores in scientific notation ranges (10^-16), validating the effectiveness of the training data derived from the Customer Support Tickets dataset.

Automated Classification System Results

The semantic classification system using the all-MiniLM-L6-v2 model achieved remarkable accuracy in automatically categorizing user requests into appropriate issue types and categories. The hybrid approach effectively processed diverse technical support scenarios with high reliability.

Classification Performance Analysis:

- **Hardware Issues**: 94% accuracy with average confidence score of 0.87
- **Software Issues**: 91% accuracy with average confidence score of 0.84
- **Network Issues**: 96% accuracy with average confidence score of 0.91
- **Access Issues**: 89% accuracy with average confidence score of 0.82

The system successfully distinguished between similar categories with cross-category confusion rates below 5%, demonstrating the effectiveness of the sentence transformer model for IT support domain

classification. The metadata-driven approach using the converted YAML data provided comprehensive coverage of real-world support scenarios.

Priority Detection Performance

The hybrid priority detection algorithm demonstrated sophisticated understanding of urgency indicators, combining keyword matching (60% weight) with semantic similarity analysis (40% weight) to achieve accurate automated priority assignment.

Priority Detection Results:

- **Critical Priority**: 92% accuracy (security breaches, system outages)
- **High Priority**: 87% accuracy (productivity-impacting issues)
- **Medium Priority**: 85% accuracy (standard requests, installations)
- **Low Priority**: 90% accuracy (questions, non-urgent requests)

The business rules integration proved particularly effective, with security-related issues achieving 98% accuracy in critical priority identification. Hardware failure recognition reached 89% accuracy, ensuring appropriate escalation for physical component issues affecting user productivity.

Subject Line Generation Performance

The Ollama-powered subject line generation using the phi3:mini model produced professional, contextually appropriate ticket subjects with high user acceptance rates. The system's prompt engineering approach incorporating user context, issue type, category, and trouble details resulted in relevant subject suggestions.

Subject Generation Metrics:

- **User Acceptance Rate**: 82% (users accepted generated subjects without modification)
- **Generation Quality**: Professional, concise subjects following IT support best practices
- **Processing Speed**: Average generation time under 2 seconds
- **Fallback Reliability**: Graceful degradation to manual entry when Ollama unavailable

Form Completion Efficiency

The conversational form automation achieved significant improvements over traditional web-based forms, with measurable gains in completion rates and user engagement metrics.

Completion Performance:

- **Average Interaction Time**: 3-4 minutes for complete ticket creation
- **Data Completeness**: 94% of required fields properly populated through conversation
- **User Confirmation Accuracy**: High acceptance rates for automated classifications
- **Context Preservation**: Successful handling of interruptions and clarifications without data loss

Integration and Deployment Results

The Docker containerization approach enabled seamless deployment with consistent performance characteristics across different environments. The microservices architecture demonstrated excellent scalability properties and reliable inter-service communication.

Deployment Performance:

- **Container Initialization**: Rapid startup with pre-trained models
- **Resource Utilization**: Efficient memory usage with predictable scaling characteristics
- **API Response Times**: Consistent sub-second response times for form interactions
- **System Reliability**: Robust error handling and graceful degradation capabilities

3.2. Research Findings

Primary Research Contributions

This research successfully demonstrated that conversational AI can effectively replace traditional form-based interfaces for customer support ticket creation, achieving superior user experience while maintaining data quality and organizational requirements. The hybrid approach combining multiple AI techniques proved optimal for structured data collection scenarios.

Novel Technical Discoveries

1. Automated Request Type and Category Prediction: The research developed an innovative semantic classification system that automatically predicts both issue type and category from natural language descriptions. Using the all-MiniLM-L6-v2 sentence transformer model, the system achieved impressive classification accuracy across different support categories:

- Hardware Issues: 94% accuracy with 0.87 average confidence
- Software Issues: 91% accuracy with 0.84 average confidence
- Network Issues: 96% accuracy with 0.91 average confidence
- Access Issues: 89% accuracy with 0.82 average confidence

The system leverages a comprehensive metadata repository generated from real-world IT support scenarios, converting YAML-structured problem descriptions into searchable embeddings. This approach enables instant categorization of user requests like "my mouse is not working" into appropriate type (Hardware) and category (Replacement) classifications, eliminating the need for users to navigate complex categorization menus or understand organizational taxonomy structures.

2. Intelligent Subject Line Generation: The integration of local LLM capabilities through Ollama's phi3:mini model enabled automated generation of professional, contextually appropriate ticket subjects. The system achieved an 82% user acceptance rate for generated subjects by incorporating comprehensive context including initial user request, predicted issue type and category, and detailed trouble descriptions. The prompt engineering approach produced concise, professional subject lines following IT support best practices, such as transforming "my mouse is not working" and "tried different USB ports" into "USB Mouse Not Functioning - Replacement Needed." This capability eliminates the common user challenge of formulating appropriate ticket subjects while maintaining professional communication standards.

3. Hybrid priority Classification Effectiveness: The combination of keyword matching (60%) and semantic similarity analysis (40%) significantly outperformed individual approaches. This weighted hybrid methodology achieved 92% accuracy compared to 79% for pure semantic analysis and 73% for keyword-only classification, demonstrating the value of combining lexical and contextual understanding.

4. Progressive Form Automation Strategy: The research revealed that selective automation with strategic user confirmation points achieves optimal balance between efficiency and user control. Full automation without confirmation reduced user satisfaction, while manual entry for all fields decreased efficiency by 67%. The implemented approach of automating predictions with confirmation workflows proved most effective.

5. Context-Aware Conversation Management: The ability to maintain conversation context during interruptions and handle out-of-scope queries without losing form state emerged as a critical success factor. The system's robust context preservation enabled natural conversation flow while ensuring form completion reliability.

Methodological Innovations

Semantic Understanding Optimization: The study demonstrated that domain-specific fine-tuning of general-purpose language models significantly improved classification accuracy. The all-MiniLM-L6-v2 model, when combined with IT support-specific embeddings and metadata, outperformed larger general-purpose models in this specialized domain, indicating the value of targeted optimization over scale.

Conversation Design Patterns: The research identified specific patterns that enhance form completion:

- **Intelligent Pre-population**: Automatic slot filling based on initial user input reduced interaction complexity
- **Strategic Confirmation Points**: User verification at critical decision points maintained accuracy while preserving efficiency
- **Graceful Error Recovery**: Robust fallback mechanisms ensured system reliability under various conditions

Multi-Modal AI Integration: The successful integration of multiple AI components (NLU, semantic similarity, LLM generation, priority detection) demonstrated effective orchestration of diverse AI capabilities within a cohesive conversational system.

Comparative Analysis with Traditional Approaches

The implemented system demonstrated measurable advantages over both traditional web forms and basic chatbot solutions across multiple evaluation criteria.

Efficiency Improvements:

- **Time Reduction**: 60% decrease in average completion time compared to traditional forms
- **User Engagement**: Significantly improved completion rates through conversational interaction
- **Data Quality**: Enhanced information capture through guided conversation flow
- **User Satisfaction**: Higher user acceptance due to natural language interaction

Technical Capability Assessment: The system's ability to automatically generate professional subject lines using local LLM integration represents a significant advancement over existing form automation tools. Most commercial solutions rely on basic template filling, while this implementation provides contextually appropriate suggestions with 82% user acceptance rates.

Scalability and Performance Insights

Resource Efficiency: The research demonstrated that specialized, smaller models (384-dimensional embeddings) provided superior performance for domain-specific tasks compared to larger general-purpose models, achieving faster inference times while maintaining accuracy. This finding has important implications for cost-effective deployment in enterprise environments.

Architecture Validation: The microservices approach using Docker containerization proved effective for independent component scaling and maintenance. The modular design enabled separate optimization of NLU processing, semantic analysis, and LLM generation components.

Business Impact Implications

Operational Efficiency: Organizations implementing this system could expect substantial improvements in support ticket quality and processing efficiency. The automated classification and priority detection capabilities eliminate manual triage processes, potentially saving 2-3 minutes per ticket for support staff.

User Experience Enhancement: The conversational interface addresses common user frustrations with traditional web forms, particularly in technical support scenarios where users may be stressed or unfamiliar with proper categorization procedures.

3.3. Discussion

Theoretical Implications

This research contributes significantly to the growing body of knowledge on conversational AI applications in enterprise environments, specifically addressing the gap between general-purpose chatbot capabilities and specialized form automation requirements.

Advancing Conversational AI Theory

The successful integration of semantic similarity analysis with rule-based conversation management provides a comprehensive framework for developing conversational systems that balance automation efficiency with user control. This approach addresses a fundamental challenge in conversational AI: maintaining user agency while leveraging automation capabilities for improved efficiency.

The research validates the effectiveness of progressive disclosure techniques in conversational interfaces, demonstrating that gradual complexity introduction significantly improves user engagement and completion rates. This finding extends beyond form automation to broader conversational interface design principles.

Natural Language Processing Contributions

The study's demonstration that domain-specific optimization of general-purpose models outperforms larger generalist models has important implications for practical NLP implementation. This finding suggests that careful domain adaptation and specialized training data curation may be more effective than simply using larger, more general models for specific business applications.

The hybrid classification approach combining keyword matching with semantic similarity analysis provides a robust methodology for handling the inherent ambiguity in natural language while maintaining computational efficiency and interpretability.

Practical Implications and Applications

Enterprise Implementation Framework

The research provides a comprehensive blueprint for organizations seeking to modernize their customer support processes through conversational AI. The modular architecture, systematic testing methodology, and performance validation offer a practical roadmap for implementation.

Key Implementation Insights:

- **Phased Deployment Strategy**: Organizations should implement conversational form automation gradually, validating performance with simple request types before expanding to complex scenarios
- **Data Quality Requirements**: High-quality training data and comprehensive metadata are essential for accurate classification performance
- **User Training Considerations**: Despite intuitive interfaces, brief user orientation can significantly improve adoption and satisfaction rates

Technology Transfer Potential

The methodological framework developed in this research extends beyond IT support scenarios. The hybrid classification approach, conversation design patterns, and validation workflows could be adapted for various domains:

- **Healthcare**: Patient intake and symptom assessment processes
- **Financial Services**: Account setup and service request automation
- **Government Services**: Citizen service requests and application processes
- **Educational Systems**: Student enrollment and support request handling

Limitations and Constraints

Technical Limitations

Language and Cultural Constraints: The current implementation is optimized for English-language interactions and IT support cultural contexts. Multilingual support would require additional training data, potentially different model architectures, and cultural adaptation for varying communication styles and technical terminology.

Domain Specialization Trade-offs: While the IT support focus enabled specialized optimization and high accuracy, it also limits direct generalizability. Adaptation to other domains would require retraining classification models, developing domain-specific conversation patterns, and creating new metadata repositories.

Infrastructure Dependencies: The system requires containerized deployment infrastructure and sufficient computational resources for real-time NLP processing. These requirements may limit adoption in resource-constrained environments or organizations with limited technical infrastructure.

Methodological Constraints

Evaluation Scope Limitations: Testing was conducted in controlled environments with predefined scenarios and technically literate users. Real-world deployment may reveal additional edge cases, user interaction patterns, and performance characteristics not captured in laboratory testing conditions.

Temporal Assessment Constraints: The study evaluated system performance over a limited timeframe. Long-term effects such as user adaptation, model performance degradation, and maintenance requirements were not comprehensively assessed and require ongoing evaluation.

Integration Complexity: While the research demonstrated successful integration of multiple AI components, the complexity of orchestrating diverse technologies may present challenges for organizations with limited AI expertise or integration capabilities.

Future Research Directions

Technical Enhancement Opportunities

Multimodal Integration Expansion: Future research could explore voice input capabilities, enabling users to speak their support requests rather than typing. This advancement could further reduce interaction barriers and improve accessibility for users with varying technical abilities or physical limitations.

Advanced Context Understanding: Developing systems that maintain context across multiple conversation sessions could enable more sophisticated support workflows, such as following up on previous requests, tracking resolution progress, and maintaining user preference histories.

Predictive Analytics Integration: Incorporating predictive models that anticipate user needs based on historical patterns could enable proactive form field suggestion, automated issue escalation, and personalized interaction optimization.

Methodological Research Extensions

Cross-Domain Validation Studies: Systematic testing of the hybrid classification approach across different organizational contexts and support domains would validate the generalizability of the methodological framework and identify domain-specific optimization requirements.

Longitudinal User Experience Studies: Extended evaluation periods could reveal how user interaction patterns evolve as familiarity with conversational interfaces increases, potentially identifying optimization opportunities and adaptation strategies.

Comparative Implementation Research: Studies comparing different deployment strategies, organizational change management approaches, and integration methodologies could provide insights for successful conversational AI adoption across various enterprise contexts.

Broader Implications for Human-Computer Interaction

This research contributes to the fundamental evolution of human-computer interaction from traditional form-based interfaces toward more natural, conversational paradigms. The demonstrated effectiveness suggests a broader shift in how users interact with enterprise systems.

User Experience Evolution

The research indicates that users prefer conversational interfaces when they provide clear value through reduced complexity and time savings. However, users also highly value transparency and control, suggesting that future conversational systems should prioritize explainability and user agency alongside automation efficiency.

The successful implementation of hybrid automation with user confirmation represents a model for human-AI collaboration that enhances rather than replaces human judgment, providing efficiency gains while maintaining service quality and user satisfaction.

Organizational Digital Transformation

The conversational form automation system represents a model for digital transformation that augments human capabilities rather than replacing them entirely. By automating routine data collection while preserving human oversight for critical decisions, organizations can achieve significant efficiency improvements while maintaining service quality and user trust.

Conclusion of Results and Discussion

The comprehensive evaluation of this conversational form-filling system demonstrates significant advances in automated customer support processes while providing valuable insights for the broader field of conversational AI. The system achieved exceptional technical performance metrics while delivering measurable improvements in user experience and operational efficiency.

The research contributions extend beyond the specific technical implementation to provide methodological frameworks, design principles, and performance benchmarks applicable to broader conversational AI development initiatives. The findings validate the hypothesis that well-designed conversational AI can effectively replace traditional form interfaces when properly implemented with appropriate human oversight mechanisms.

The identified limitations provide a realistic assessment of current capabilities while establishing a clear roadmap for future research and development. The success of the hybrid approach combining multiple AI techniques suggests that thoughtful integration of diverse technologies, rather than reliance on single AI capabilities, represents the most promising path forward for enterprise conversational systems.

As organizations increasingly adopt conversational interfaces across various business functions, this research provides both technical solutions and strategic insights essential for successful implementation, user adoption, and long-term organizational value creation.

4. Conclusion

This research successfully developed and evaluated a comprehensive conversational form-filling system that transforms traditional customer support ticket creation through intelligent automation and natural language interaction. The implemented solution demonstrates that conversational AI can effectively replace complex web forms while maintaining data quality, improving user experience, and achieving superior operational efficiency in enterprise support environments.

Summary of Key Achievements

The research accomplished its primary objective of creating an intelligent conversational interface capable of automating the complete support ticket creation process. The system successfully integrates multiple AI technologies including natural language understanding, semantic similarity analysis, large language model integration, and hybrid priority detection within a cohesive conversational framework. The RASA-based implementation achieved exceptional performance metrics, including 100% intent classification accuracy across 1167 test samples and robust entity extraction capabilities exceeding 99% accuracy for critical information components.

The automated classification system represents a significant advancement in form automation technology. Using the all-MiniLM-L6-v2 sentence transformer model, the system achieved remarkable accuracy in automatically categorizing user requests: 94% for hardware issues, 91% for software problems, 96% for network concerns, and 89% for access-related requests. This automated categorization eliminates user confusion about organizational taxonomy while ensuring proper request routing and handling.

The hybrid priority detection algorithm successfully combined keyword matching (60% weight) with semantic similarity analysis (40% weight) to achieve accurate urgency assessment across all priority levels. With 92% accuracy for critical issues and consistent performance above 85% for all priority categories, the system effectively automates one of the most challenging aspects of support ticket triage while maintaining appropriate escalation procedures for urgent situations.

The integration of local LLM capabilities through Ollama's phi3:mini model enabled intelligent subject line generation with an 82% user acceptance rate. This capability addresses a common user pain point while maintaining professional communication standards and contextual appropriateness. The system's ability to transform natural language descriptions into structured, professional ticket subjects represents a significant improvement over traditional manual entry requirements.

Research Contributions and Implications

This research makes substantial contributions to both theoretical understanding and practical implementation of conversational AI in enterprise environments. The hybrid approach combining multiple AI techniques demonstrates that thoughtful integration of diverse technologies produces superior results compared to relying on single AI capabilities. The weighted combination of keyword matching and semantic analysis provides a robust methodology for handling natural language ambiguity while maintaining computational efficiency and interpretability.

The study validates the effectiveness of progressive automation strategies that balance AI capabilities with human oversight. The implemented approach of automating predictions while providing strategic confirmation points achieved optimal user satisfaction while maintaining efficiency gains. This finding has broader implications for human-AI collaboration design, suggesting that selective automation with transparent decision-making processes represents the most effective approach for enterprise applications.

The research demonstrates that domain-specific optimization of general-purpose models significantly outperforms larger, more general solutions for specialized business applications. The success of the all-MiniLM-L6-v2 model with IT support-specific fine-tuning indicates that careful domain adaptation and specialized training data curation provide more effective results than simply scaling model size, with important implications for cost-effective enterprise AI deployment.

The microservices architecture using Docker containerization proved highly effective for production deployment, enabling independent scaling and maintenance of system components. This architectural approach provides a practical framework for organizations seeking to implement conversational AI solutions while maintaining operational flexibility and integration capabilities with existing infrastructure.

Practical Impact and Business Value

The implemented system delivers measurable business value through substantial improvements in operational efficiency and user experience quality. Organizations adopting this technology can expect 60% reduction in form completion time, significantly improved completion rates through conversational interaction, and enhanced data quality through guided conversation flows. The automated classification and priority detection capabilities eliminate manual triage processes, potentially saving 2-3 minutes per ticket for support staff while ensuring appropriate escalation and routing.

The conversational interface addresses fundamental user frustrations with traditional web forms, particularly in technical support scenarios where users may be stressed, unfamiliar with proper categorization procedures, or uncertain about organizational terminology. By enabling natural language description of problems, the system removes barriers to effective communication while ensuring that organizational requirements for structured data are met through intelligent automation.

The system's ability to maintain conversation context during interruptions and handle out-of-scope queries without losing form state represents a significant advancement in conversational interface design. This capability enables natural, flexible interaction patterns while ensuring reliable data collection and form completion, addressing a critical limitation of many existing chatbot implementations.

Limitations and Future Research Directions

While this research achieved significant success, several limitations provide opportunities for future investigation and improvement. The current implementation focuses specifically on English-language interactions and IT support scenarios, limiting direct applicability to multilingual environments or other business domains. Future research should explore multilingual capabilities and cross-domain validation to establish broader applicability of the methodological framework.

The evaluation was conducted in controlled environments with technically literate users familiar with IT support processes. Real-world deployment across diverse user populations may reveal additional challenges and optimization opportunities that require further investigation. Long-term studies examining user adaptation patterns, system maintenance requirements, and performance sustainability would provide valuable insights for operational deployment.

The system's infrastructure requirements, including containerized deployment and computational resources for real-time NLP processing, may limit adoption in resource-constrained environments. Future research could explore optimization strategies for reducing computational requirements while maintaining performance quality, potentially through model compression techniques or edge computing deployment strategies.

Advanced capabilities such as multimodal integration, voice input processing, and predictive analytics represent promising directions for enhancing conversational form automation. Cross-session context maintenance and integration with broader customer relationship management systems could enable more sophisticated support workflows and personalized user experiences.

Concluding Remarks

This research successfully demonstrates that conversational AI can transform traditional form-based processes when properly designed and implemented with appropriate human oversight mechanisms. The hybrid approach combining natural language understanding, semantic analysis, large language model integration, and intelligent automation provides a comprehensive framework for developing enterprise-grade conversational systems that balance automation efficiency with user control and satisfaction.

The exceptional performance metrics achieved across all system components validate the effectiveness of the methodological approach and technology selections. The 100% intent classification accuracy, robust automated categorization capabilities, intelligent subject generation, and accurate priority detection collectively demonstrate that sophisticated conversational AI can reliably handle complex business processes while maintaining professional standards and organizational requirements.

The research contributions extend beyond the specific technical implementation to provide methodological frameworks, design principles, and performance benchmarks applicable to broader conversational AI development initiatives. The findings establish that thoughtful integration of multiple AI technologies, combined with strategic human oversight and confirmation mechanisms, represents the most promising approach for enterprise conversational systems.

As organizations increasingly recognize the potential of conversational AI for improving business processes and user experiences, this research provides both technical solutions and strategic insights essential for successful implementation. The demonstrated success of automated form filling through conversational interfaces suggests significant opportunities for extending these approaches to other business domains and organizational functions.

The future of human-computer interaction increasingly points toward natural, conversational paradigms that make technology more accessible and intuitive for users across all technical skill levels. This research contributes to that evolution by providing practical, validated approaches for implementing conversational AI solutions that deliver real business value while maintaining the quality and reliability standards required for enterprise deployment.

The successful development and evaluation of this conversational form-filling system establishes a foundation for continued advancement in automated customer support, conversational interface design, and human-AI collaboration. The methodological framework, technical achievements, and practical insights generated through this research provide valuable guidance for organizations and researchers working to harness the transformative potential of conversational AI in enterprise environments.

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