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Research on Improving the Quality of Online Customer Support Using Artificial Intelligence

Master Graduation Thesis

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Abbreviations

The abbreviations used in this document are described as follows:

A/B testing: Split Testing

ADL: Analytical Decision List

AI: Artificial Intelligence

AMOS: Analysis of Moment Structures

ANOVA: Analysis of Variance

AVE: Average Variance Extracted

BPMN: Business Process Model and Notation

BEET: Behavioral Emotion Engagement Trigger

CBR: Case-Based Reasoning

CFI: Comparative Fit Index

ChatGPT: Chat Generative Pre-Trained Transformer

CO: Conversational Optimization

CRM: Customer Relationship Management

CSAT: Customer Satisfaction Score

CSR: Corporate Social Responsibility

DNN: Deep Neural Network

ECI: Employee–customer identification

FAQs: Frequently Asked Questions

GPT-3: Generative Pre-trained Transformer 3

HAI: Human-AI Interaction

HCI: Human-Computer Interaction

IDE: Integrated Development Environment

LLM: Large Language Model

MAE: Mean Absolute Error

ML: Machine Learning

NLP: Natural Language Processing

NPS: Net Promoter Score

QA: Quality Assurance (or Question Answering, depending on context)

Q&A: Questions and Answers

RAG: Retrieval-Augmented Generation

RMSEA: Root Mean Square Error of Approximation

RMSE: Root Mean Square Error

ROI: Return on Investment

SAC: SAP Analytics Cloud

SAP: Systems, Applications, and Products in Data Processing

SEM: Structural Equation Modeling

SERVQUAL: Service Quality

SOSE: Service-Oriented Systems Engineering

SPSS: Statistical Package for the Social Sciences

SSRL: Socially shared regulation of learning

TAM: Technology Acceptance Model

UX: User Experience

1. Introduction

In the rapidly evolving digital landscape, the quality of online customer support plays a pivotal role in shaping customer satisfaction, loyalty, and overall brand perception. Traditional customer support systems often struggle to meet the growing expectations for timely, accurate, and personalized assistance due to limitations in scalability, response time, and consistency. These challenges are further compounded by the increasing volume of customer queries and the diversity of user needs, making it difficult for human agents to maintain efficiency and quality simultaneously.

The aim of this research is to develop AI-driven methodologies and frameworks to improve online customer support. It focuses on addressing challenges like response delays, scalability, and personalization. By leveraging AI technologies such as chatbots and machine learning, the goal is to enhance operational efficiency and customer satisfaction. Ultimately, the research seeks to create innovative solutions that elevate the overall quality of customer support services.

The first task involves identifying key quality gaps and challenges in existing customer support systems. This includes evaluating system weaknesses such as response delays, generic interactions, and scalability issues that impact overall efficiency. By gathering user feedback, analyzing performance metrics, and understanding common pain points, the aim is to pinpoint areas requiring immediate attention. This process helps in recognizing specific limitations and identifying opportunities for improvement. The insights gained from this task form the foundation for developing more effective customer support solutions that better meet customer expectations.

The second task investigates the potential of AI technologies in addressing the challenges identified in the first task. It explores how AI tools like chatbots, natural language processing, and machine learning algorithms can enhance customer support capabilities. The task focuses on assessing the ability of these AI-driven methods to improve response accuracy, streamline interactions, and personalize the customer experience. Successful case studies are also analysed to understand how AI has been implemented effectively in similar contexts. This helps in determining the best practices and suitable AI technologies for improving customer support systems.

The third task is dedicated to designing and testing AI-driven solutions that address the challenges discovered in the previous tasks. It involves creating prototypes that integrate AI technologies to enhance response accuracy, scalability, and personalized interactions. These prototypes are tested in real-world customer support environments to evaluate their performance and effectiveness. Based on feedback from customers and support teams, the solutions are refined to ensure optimal efficiency, customer satisfaction, and adaptability to different business needs. The task emphasizes continuous improvement, ensuring that the AI-driven solutions evolve to meet growing demands.

The problem of ineffective online customer support arises from limitations such as delayed responses, lack of personalization, and challenges in scaling operations to meet increasing customer demands (Järvelä et al., 2023). Despite advancements in technology, traditional support systems often fail to address these issues, leading to customer dissatisfaction and operational inefficiencies. Current solutions rely heavily on manual processes or basic automation, which are inadequate for handling complex customer needs or providing seamless experiences(Wang et al., 2020). This gap between customer expectations and service capabilities highlights the need for innovative approaches to enhance the quality of online customer support.

The proposed solution to address the problem of ineffective online customer support is to leverage Artificial Intelligence (AI) technologies such as chatbots, natural language processing (NLP), and machine learning (Nirala et al., 2022). These technologies can improve response efficiency by automating routine inquiries, enhance personalization through advanced customer intent analysis, and ensure scalability by handling high volumes of interactions simultaneously. By integrating AI-driven solutions tailored to address specific challenges like response delays and generic interactions, businesses can streamline their support processes while maintaining customer satisfaction (Esh, 2024). The solution aims to balance automation and human involvement, ensuring a seamless, efficient, and user-friendly customer support experience.

1.1 Investigation Object

The investigation object of the research is the improvement of online customer support using AI technologies such as NLP, Machine learning, and chatbots. It aims to automate support processes, enhance response accuracy, and deliver personalized interactions focusing on increasing customer satisfaction, operational efficiency, and system scalability.

1.2 The Aim and Tasks of the Thesis

The aim of the research is to enhance online customer support by addressing response delays, lack of personalization, and scalability. It focuses on improving customer satisfaction using AI technologies like chatbots, NLP, and machine learning, while expanding system capabilities through automation and balancing human involvement.

The main tasks for the research are as follows:

1. **Analysing Limitations of Existing Customer Support Systems:** To identify key quality gaps and challenges by understanding the weaknesses and areas needing improvement in current systems.
2. **Exploring AI Technologies and Their Applications in Customer Support:** To determine the most effective tools and techniques for improving service quality by identifying and evaluating the AI methods that can address the identified challenges.

3. **Designing and Testing AI-Driven Solutions:** To address identified challenges, such as response accuracy, personalization, and user satisfaction, by focusing on developing and validating practical AI solutions to enhance the quality of online customer support.

1.3 Novelty of the Topic

The novelty of this topic lies in its focus on leveraging cutting-edge AI technologies, such as natural language processing and machine learning (Mousa et al., 2024), to address evolving customer expectations in online support. Unlike traditional methods, AI-driven approaches offer real-time personalization, improved response accuracy, and scalability for diverse customer needs. This research contributes to bridging the gap between automation and human-like interaction (Graef et al., 2021), a critical challenge in modern customer service.

1.4 Relevance of the Topic

Improving the quality of online customer support is essential in today's digital age, where customers demand faster responses, personalized experiences, and seamless service. Traditional systems often fail to meet these expectations, leading to dissatisfaction and loss of loyalty. With the rise in online interactions, the need for scalable and efficient support has become more urgent.

AI technologies like chatbots and natural language processing offer transformative potential by automating tasks, enhancing personalization, and improving efficiency. This research is crucial for helping businesses stay competitive, meet customer expectations, and develop innovative solutions to address existing gaps in customer support systems. With the growing demand for seamless customer experiences, this research addresses a critical area for improving customer satisfaction and retention.

1.5 Research Methodology

This study uses an exploratory and applied research methodology to improve the quality of online customer support by integrating AI technologies such as Natural Language Processing (NLP), Machine Learning (ML), and conversational agents. The approach begins with analyzing current support systems in the e-commerce domain to identify key limitations like delayed responses, lack of personalization, and scalability issues. It then evaluates existing AI techniques including intent detection, sentiment analysis, and named entity recognition to assess their effectiveness in automating support interactions. Building on these insights, a hybrid framework is developed using transformer-based NLP models and domain-specific knowledge retrieval, inspired by Retrieval-Augmented Generation (RAG) principles, to ensure accurate, personalized, and context-aware responses. The final phase involves testing the system using real-world data, with performance measured through accuracy, response time, and customer satisfaction, enabling a comprehensive validation of the proposed solution.

1.6 Scientific Value of the Thesis

Task 01: Analyzing Limitations of Existing Customer Support Systems

This task contributes scientifically by systematically identifying and categorizing the core deficiencies in current customer support systems—such as delayed response times, lack of personalization, and limited scalability. Through structured analysis, it generates a comprehensive framework of pain points that affect customer satisfaction and operational efficiency. This foundational understanding is essential for framing research questions, setting performance benchmarks, and defining design requirements for next-generation support technologies. The outcome of this task ensures that subsequent solutions are grounded in real-world challenges, enhancing both relevance and applicability.

Task 02: Exploring AI Technologies and Their Applications in Customer Support

The second task advances the scientific discourse by critically evaluating state-of-the-art AI technologies—including chatbots, natural language processing (NLP), and machine learning—for their applicability in customer support contexts. This exploration not only identifies the capabilities and limitations of each technology but also compares their effectiveness in addressing the pain points outlined in Task 01. The task contributes to knowledge by synthesizing interdisciplinary research on AI applications and offering a taxonomy of AI-driven approaches tailored to customer service. These insights lay the groundwork for informed, evidence-based design choices in AI integration.

Task 03: Designing and Testing AI-Driven Solutions

This task adds empirical value to the research by developing and experimentally validating AI-based prototypes—such as intelligent chatbots and NLP-enabled systems—within real or simulated customer service environments. It bridges the gap between theoretical potential and practical implementation by collecting performance data related to response accuracy, personalization, and user satisfaction. The findings contribute to both applied AI research and service design by demonstrating measurable improvements over traditional systems. Furthermore, the task informs scalability strategies, offering a roadmap for deploying AI solutions in diverse, high-demand customer service settings.

1.7 Main Results of the Thesis

The main results of the thesis:

1. **Analysing Limitations of Existing Customer Support Systems**

   This task reveals the primary weaknesses in current customer support systems, including slow response times, a lack of personalized service, and scalability challenges. These findings highlight critical issues that impact customer satisfaction and service efficiency. The analysis underscores the importance of improving both technological infrastructure and service processes to better meet customer expectations.

2. **Exploring AI Technologies and Their Applications in Customer Support**

   The key outcome of this task is the identification of AI technologies like chatbots, natural language processing, and machine learning, which can effectively address the limitations observed in existing support systems. The research demonstrates how these AI tools can improve response speed, offer personalized interactions, and handle a higher volume of customer queries efficiently, showing AI's potential to enhance customer service.

3. **Designing and Testing AI-Driven Solutions**

   The results of this task involve the creation and successful deployment of AI-driven solutions, such as chatbots and NLP systems, in real-world customer support settings. These AI systems were shown to improve response accuracy, provide personalized assistance, and increase customer satisfaction. The testing phase confirmed that AI technologies could be practically applied to overcome challenges identified in earlier tasks, offering scalable improvements to customer support.

1.8 Structure of the Work

1. **Introduction:** Introduces challenges in online customer support and highlights AI's transformative potential to improve efficiency, scalability, and personalization.
2. **Literature Review:** Reviews existing studies on AI in customer support, identifies strengths, limitations, and gaps to guide the research focus.
3. **Proposed Methodology:** Presents a systematic framework that integrates NLP and machine learning techniques to enhance response accuracy, personalization, and support scalability. It outlines the stages of data preprocessing, intent and sentiment recognition, contextual information retrieval, intelligent response generation, and performance evaluation, highlighting a hybrid AI approach that balances automation with human-like interaction quality.
4. **Initial Experimental Results and Analysis:** This section describes the experimental setup using real-world or simulated customer support datasets, along with evaluation metrics such as response accuracy, resolution time, and customer satisfaction. It provides a comparative analysis against baseline rule-based and non-adaptive models, discussing practical effectiveness, observed improvements, and limitations.
5. **Conclusion and References:** Concludes the findings from the literature review, proposed methodology, and initial experiments, confirming the potential of AI in improving customer support quality. The section concludes with key insights, future directions, and a comprehensive list of references cited throughout the thesis. References used throughout the thesis are listed in the references section.

2. Related work Analysis

2.1 Main concepts

The main concept of this research revolves around improving the quality of online customer support through the integration of Artificial Intelligence (AI) technologies. As digital services grow more prevalent, customer expectations for immediate, accurate, and personalized support are also rising. Traditional customer support systems, typically reliant on human agents struggle to meet these evolving demands due to constraints in scalability, response speed, consistency, and cost. AI offers a transformative opportunity to address these gaps by automating repetitive tasks, improving information retrieval, and offering dynamic and intelligent interaction.

Understanding Customer Support

Customer support refers to the services provided by companies to help customers use and understand their products or services effectively. It includes answering questions, resolving issues, processing returns or complaints, and offering product recommendations or guidance. High-quality customer support can significantly impact user satisfaction, brand loyalty, and business growth.

Key goals of customer support include:

- Providing timely and accurate responses.
- Enhancing the customer experience with personalized solutions.
- Ensuring customer retention and brand advocacy.
- Reducing the burden on human support staff through intelligent automation.

Traditional models, such as call centers and email-based helpdesks, are increasingly being replaced or augmented by **AI-powered systems**, which include chatbots, voice assistants, automated ticketing systems, and knowledge base integrations.

AI in Customer Support

AI technologies such as **Natural Language Processing (NLP)**, **Machine Learning (ML)**, and **Conversational Agents** (e.g., chatbots) are used to automate customer interactions and improve the user experience. NLP enables machines to understand and process human language, while ML allows systems to learn from historical interactions and improve over time. Together, they enable intelligent systems that can interpret customer intent, retrieve relevant information, and provide coherent, context-aware responses.

In this research, AI is applied not just to respond to simple queries but also to handle complex interactions, detect customer emotions or sentiment, and escalate issues to human agents when necessary, thus supporting a **hybrid human-AI model** that balances automation with empathy and accuracy.

Domain Focus: E-Commerce Customer Support

To contextualize the research, this study focuses specifically on **customer support in the e-commerce domain**. E-commerce businesses operate in a highly competitive and customer-centric environment, where service quality is a key differentiator. Online retailers handle a large volume of daily queries related to product details, payment issues, delivery tracking, return policies, and technical support. These inquiries vary widely in complexity and urgency, making the e-commerce sector an ideal candidate for AI-driven customer support solutions.

Challenges in E-Commerce Customer Support

- High volume of inquiries during peak seasons (e.g., Black Friday, holiday sales).
- Scalability issues, as human agents cannot respond to thousands of simultaneous queries.
- Generic responses that frustrate customers expecting personalized service.
- Long resolution times, especially for returns, refunds, or account-related issues.
- Multichannel support demands, including website chat, mobile apps, social media, and email.

Opportunities for AI in E-Commerce

AI can significantly streamline support processes in e-commerce by:

- Using chatbots to handle FAQs and order tracking in real-time.
- Employing NLP to understand customer intent across various languages and dialects.
- Applying recommendation systems to upsell or cross-sell based on user behavior and preferences.
- Integrating AI with CRM systems to provide agents with customer history and insights for more effective resolution.
- Leveraging sentiment analysis to detect and prioritize dissatisfied customers for faster intervention.

For example, an AI-powered chatbot in an e-commerce platform can automatically respond to order status queries, initiate a return process based on eligibility criteria, and even detect frustration in a user's tone to escalate the issue to a human agent. This not only improves customer experience but also reduces operational costs and improves agent productivity.

2.2 Related works on Improving the Quality of Online Customer Support using AI

In (Nirala et al., 2022), provides a comprehensive survey on the use of AI-powered chatbots for delivering customer and public administration services, aiming to improve accessibility, efficiency, and customer satisfaction. The main contribution of the approach is its exploration of AI-driven chatbots as a versatile tool for automating service delivery in both private and public sectors, enhancing service accessibility. One advantage of this method is its ability to handle a wide range of inquiries, providing quick responses, while a disadvantage could be the challenge of accurately interpreting complex or nuanced user requests. The research applies various AI techniques, including Natural Language Processing (NLP), machine learning, and conversational AI algorithms, to evaluate chatbot effectiveness. Verification is done through surveys and case studies, gathering feedback from users and administrators on the chatbot's performance. Experiments are performed to assess chatbot response accuracy and efficiency in different service contexts. Tools such as Python, NLP libraries, and AI development frameworks are used for implementation, with datasets consisting of user interactions, feedback, and service queries. This paper contributes to my Master Thesis by offering insights into the integration of AI chatbots in service delivery, providing a foundation for future research on improving chatbot design for customer and public administration services.

In (Järvelä et al., 2023), explore the collaboration between human and artificial intelligence (AI) in fostering socially shared regulation of learning (SSRL). The study examines how AI tools can support group learning by promoting metacognition, shared goal-setting, and collaborative monitoring. It highlights the potential of AI to analyze interaction patterns and provide real-time feedback, enhancing group dynamics and self-regulation processes. The authors emphasize that effective collaboration requires balancing AI's analytical strengths with human creativity and contextual understanding. They also discuss the ethical implications of AI in learning, including concerns about privacy and the risk of over-reliance on technology. The study provides a framework for integrating AI in educational contexts to augment human abilities rather than replace them. By aligning AI's capabilities with pedagogical goals, the research showcases a pathway to enhance collaborative learning outcomes. It also identifies challenges, such as the need for educators to develop AI literacy. The findings underline the importance of designing AI systems that are adaptable, transparent, and aligned with human values.

In (Yue & Li, 2023), explores how different types of human-AI collaboration influence consumer perceptions and their intention to use AI-driven products or services. The research focuses on how responsibility for outcomes is attributed between humans and AI, affecting trust and evaluation. The study suggests that when consumers perceive AI as more autonomous and accountable, they tend to evaluate the technology more positively, leading to greater usage intention. Conversely, when responsibility is more heavily placed on human collaborators, consumers may express concerns about reliability and control. The findings highlight the importance of clear responsibility distribution in AI systems to ensure consumer trust. The research also identifies that the type of collaboration (e.g., AI as a decision support tool vs. fully autonomous AI) shapes how consumers view AI's role in delivering outcomes. The paper concludes by emphasizing the need for transparent communication and design strategies to optimize human-AI collaboration, fostering better user acceptance and engagement.

In (Nazarov et al., 2020), presents a framework for building technology and predictive analytics models within the SAP Analytics Cloud (SAC) digital service, aiming to optimize data-driven decision-making processes. The main contribution is the development of a scalable model that integrates various data sources and predictive analytics techniques, enhancing the forecasting and analytical capabilities of businesses. One advantage of this approach is its ability to provide real-time, actionable insights with minimal latency, while a disadvantage may be the complexity of deploying and maintaining such models in large-scale environments. The research applies machine learning algorithms, data preprocessing techniques, and statistical models to build accurate predictive systems. Verification is carried out through case studies where the models are tested in real-world business scenarios to evaluate their performance and impact. Several experiments assess the models' effectiveness in predicting business outcomes such as sales trends and market behavior. Tools like SAP Analytics Cloud, Python, and R are used for implementation, with datasets consisting of historical business data and performance metrics. This paper contributes to my Master Thesis by offering a practical approach to predictive analytics in cloud-based environments, providing a solid foundation for further research in enterprise analytics and decision support systems.

In (Ushakova et al., 2023), The publication introduces the Analytical Decision List (ADL) algorithm for managing customer reactions to marketing campaigns, aiming to enhance decision-making by analyzing customer responses and predicting future behaviors. The main contribution of this approach is its ability to generate actionable insights from customer data, improving campaign effectiveness by targeting the right segments with tailored strategies. One advantage is its precision in predicting customer behavior based on past interactions, while a disadvantage could be its reliance on high-quality, structured data, which may be difficult to obtain. The research applies decision tree algorithms, classification techniques, and data mining methods to process and analyze customer feedback. Verification methods include experiments, where the ADL algorithm is tested on real marketing campaign data to evaluate its predictive accuracy and efficiency. Several experiments assess the algorithm's ability to predict customer responses and optimize marketing strategies. Tools like Python, R, and decision tree libraries are used for the implementation, with datasets comprising customer demographic information, interaction logs, and campaign response data. This paper contributes to my Master Thesis by offering a practical method for improving marketing decision-making through data-driven insights, providing a foundation for future research in customer analytics and marketing optimization.

In (Schecter et al., 2023), publication introduces Vero, an accessible method for studying human-AI teamwork, designed to facilitate understanding and improve collaboration between humans and artificial intelligence systems. The primary contribution is the development of a framework that simplifies the process of studying and analyzing human-AI interactions, making it more accessible for researchers and practitioners. The approach's main advantage is its user-friendly design, enabling easy deployment in various domains, while its potential disadvantage lies in its reliance on predefined interaction models that may not be adaptable to all contexts. The research applies a combination of AI modeling, human-computer interaction principles, and collaboration algorithms to enhance teamwork efficiency. Verification of the method is carried out through experiments in controlled environments, testing the system's ability to foster effective teamwork. Various experiments were conducted to evaluate the system’s performance in tasks requiring human-AI collaboration. Tools such as Python and machine learning libraries are used to implement the Vero system, with datasets derived from simulated teamwork scenarios. This paper contributes to my Master Thesis by providing an accessible method for evaluating human-AI collaboration, offering a foundation for future research on improving teamwork in AI applications.

In (Tutul et al., 2023), investigate how AI technologies can aid humans in detecting deceptive speech. The research explores the integration of machine learning algorithms to analyze speech patterns, vocal cues, and linguistic characteristics that may indicate deception. However, the study emphasizes that human expertise is critical for interpreting contextual information, non-verbal signals, and the overall communication environment, which AI alone may overlook. The findings suggest that combining AI’s ability to process large datasets with human judgment leads to more accurate and reliable deception detection. The paper also highlights the ethical concerns and challenges of deploying AI in sensitive contexts like law enforcement or security, especially around privacy and potential bias. Ultimately, Tutul et al. (2023) propose a collaborative framework where AI acts as a tool to enhance human decision-making, rather than replacing it, to ensure ethical and effective detection of deceptive speech.

In (Graef et al., 2021)**,** publication presents a long-term feedback-based approach to human-machine collaboration in online customer service, aiming to improve service quality through continuous learning from customer interactions. The main advantage of this approach is its ability to adapt and evolve over time by incorporating feedback into the system, ensuring better customer satisfaction and more effective service delivery. A potential disadvantage is the reliance on constant feedback, which may require substantial resources to maintain and process. The research applies reinforcement learning algorithms and natural language processing (NLP) techniques to enhance the machine’s decision-making process based on customer feedback. Verification is done through a series of experiments where the system is tested in real-world customer service scenarios. Tools like Python, TensorFlow, and various NLP libraries are used for implementation, while datasets include historical customer service interactions. This paper contributes to my Master Thesis by providing an innovative framework for integrating human feedback into machine learning systems, offering valuable insights for future research in customer service automation and AI-driven interactions.

In (Petrescu & Krishen, 2023), the authors explore the synergy between human expertise and AI in the field of marketing analytics. The research focuses on how AI-driven tools, such as machine learning algorithms and predictive analytics, can process vast amounts of consumer data to uncover patterns, trends, and insights that may not be immediately apparent to humans. However, the study emphasizes that human intuition, creativity, and strategic thinking are essential for interpreting these insights in a meaningful way and making informed marketing decisions. The authors argue that the combination of AI's data processing power with human contextual understanding results in "hybrid intelligence," which improves decision-making and enhances marketing effectiveness. The paper also discusses the challenges of integrating AI into marketing, including the need for proper training, trust-building, and ethical considerations around data usage. Ultimately, Petrescu and Krishen (2023) propose that human-AI collaboration can revolutionize marketing practices by leveraging the strengths of both human and artificial intelligence.

In (Wang et al., 2020), the authors explore the evolution of collaboration from human-human interaction to human-AI partnerships. The paper examines how AI systems can be designed to work alongside humans, not just as tools but as collaborative partners that enhance human capabilities. The study emphasizes the importance of designing AI systems that understand human intentions, adapt to users' needs, and provide feedback in ways that foster trust and effective teamwork. Wang et al. (2020) highlight key factors for successful human-AI collaboration, including transparency, interpretability, and the ability for AI to learn from human input. The authors also discuss the challenges of ensuring that AI systems are intuitive and aligned with human values, particularly in decision-making contexts. The paper advocates for a user-centric design approach, ensuring that AI systems complement human expertise and improve overall performance. Ultimately, the study envisions a future where AI systems are integral collaborators, enhancing human productivity and decision-making across various domains.

In (Adam et al., 2021), study investigates how AI-based chatbots in customer service influence user compliance with suggested actions during digital interactions. The authors focus on chatbot design elements such as tone, personalization, and trustworthiness, analysing their effects on user behaviour. Key findings show that chatbots using empathetic language and contextual awareness are more likely to influence user compliance positively. The research applies experimental methods, including surveys and controlled interactions, to assess user responses. The paper discusses advantages such as scalability and consistent service delivery, while noting risks like over-automation leading to customer frustration. Verification involves measuring behavioural responses and compliance rates across user segments. Technologies include NLP engines and AI dialogue systems. This paper contributes to my thesis by highlighting psychological factors in human-computer interaction, especially in persuasive system design for customer support.

In (Nicolescu & Tudorache, 2022), paper offers a systematic literature review focusing on human-computer interaction (HCI) in AI chatbot-based customer service. It categorizes prior research into themes like user experience, interaction quality, dialogue management, and emotional intelligence in chatbots. The authors identify important design attributes such as tone, turn-taking efficiency, and escalation mechanisms. Experiments and studies reviewed show that users favour chatbots that are intuitive, responsive, and emotionally aware. While benefits include 24/7 availability and reduced service costs, challenges involve handling complex queries and maintaining coherent conversations. Verification is based on user satisfaction scores and usability testing. Tools used include qualitative coding frameworks and interaction logs. This review supports my Master Thesis by providing insights into interaction design and user behaviour in AI-driven systems.

In (Kappi & Marlina, 2023), empirical study explores the impact of chatbot services on customer satisfaction in online retail environments. The authors analyse factors such as response accuracy, personalization, availability, and conversational tone. Results show a strong link between chatbot performance and customer satisfaction, especially in query resolution and order tracking tasks. One key advantage of chatbots is their ability to provide instant responses, while limitations include difficulty in understanding complex issues. Verification involves surveys and user feedback analysis across various e-commerce platforms. Technologies include rule-based bots and AI-enhanced virtual assistants. This research aligns with my thesis by highlighting the measurable impact of chatbot quality on customer loyalty and perceived service effectiveness.

In (Kashyap et al., 2022), review paper examines a wide range of AI applications in e-commerce, including recommendation systems, chatbots, dynamic pricing, fraud detection, and inventory management. It outlines various technical methods like machine learning, deep learning, and NLP while also discussing business outcomes such as improved personalization and operational efficiency. The authors propose a research agenda emphasizing ethical AI, system interoperability, and small business adoption. Verification includes a synthesis of empirical studies and application case reviews. Tools range from TensorFlow to business intelligence platforms. This paper supports my thesis by providing a macro-level understanding of how AI transforms e-commerce, emphasizing trends relevant to customer service automation.

In (Tiutiu & Dabija, 2023), paper focuses on the role of AI in enhancing customer experience in online retail through tools like chatbots, recommendation engines, and visual search. The authors detail implementation strategies and assess their effectiveness using metrics such as customer retention and satisfaction scores. Key advantages include improved personalization and reduced response time, while challenges involve data privacy and integration complexity. Verification is achieved through case studies of major online retailers. Technologies include machine learning models, recommender systems, and cloud platforms. The study contributes to my thesis by illustrating how AI tools directly affect customer experience, providing a foundation for analysing chatbot impact.

In (Hsu & Lin, 2023), study analyses the factors influencing user satisfaction and loyalty toward customer service chatbots. It proposes a model combining technical (response speed, accuracy) and emotional (empathy, tone) dimensions. Surveys and interaction logs are used to validate this model, with results showing that trust and perceived social presence significantly affect loyalty. Advantages include scalable service delivery and improved customer engagement, while disadvantages may arise from unmet expectations in complex scenarios. Verification involves structural equation modelling and behavioural analysis. Tools used include survey instruments and chatbot interaction data. This paper aids my thesis by providing a user-centric framework for evaluating chatbot performance.

In (F. L. Li et al., 2020), paper introduces AliMeKG, a large-scale domain-specific knowledge graph developed by Alibaba for e-commerce applications. It details the construction process, including entity extraction, relationship mapping, and ontology development. The graph supports intelligent Q&A, product recommendation, and semantic search functionalities. One key benefit is improved chatbot understanding through enriched domain context, though maintaining such a system at scale poses challenges. Verification involves comparing task performance before and after knowledge graph integration. Tools include Python, graph databases, and Alibaba's proprietary AI platforms. This paper contributes to my thesis by showcasing how structured knowledge can enhance chatbot intelligence and accuracy.

In (Pandya & Mahavidyalaya, 2023), paper explores the use of Lang Chain, a framework for building modular applications with large language models, to automate customer service. The authors describe a pipeline combining retrieval, generation, and memory modules to handle customer queries. Key advantages include flexibility, real-time responsiveness, and improved answer relevance. Drawbacks include potential hallucination and complexity in multi-turn dialogue handling. Verification includes case implementation and testing with synthetic and real queries. Tools used are Lang Chain, OpenAI APIs, and cloud-based vector stores. This study supports my thesis by demonstrating practical architectures for integrating LLMs into customer service chatbots.

In (Wibowo et al., 2020), paper reviews the deployment of chatbots in e-commerce customer service, analysing their effectiveness in handling tasks like order inquiries, payment issues, and return policies. The authors evaluate performance through metrics like response accuracy, resolution time, and user satisfaction. Key advantages include 24/7 support and reduced operational cost, while limitations involve handling emotionally charged or complex queries. Verification includes surveys, usability tests, and customer feedback. Tools include chatbot development frameworks and CRM integration platforms. This paper contributes to my thesis by demonstrating the direct impact of chatbot features on service efficiency and consumer trust.

In (Ashfaq et al., 2020), paper proposes a theoretical model to explain users' satisfaction and continued use of AI-powered chatbots. It integrates concepts from the Technology Acceptance Model, Expectation Confirmation Theory, and social presence theory. Data is collected via user surveys after chatbot interactions. Findings reveal that perceived usefulness, empathy, and trust significantly influence satisfaction and intention to reuse. Advantages include predictive insights for chatbot design, while limitations involve potential model overfitting and demographic variance. Verification uses structural equation modelling. Tools include SPSS and AMOS for data analysis. This study enriches my thesis by linking psychological and behavioural factors to chatbot retention metrics.

In (Khrais, 2020), paper investigates how AI technologies like recommendation systems and dynamic pricing algorithms shape consumer demand in e-commerce. The authors argue that AI not only responds to demand but also creates it through predictive targeting and personalized suggestions. Benefits include increased conversion rates and customer satisfaction, while risks involve data misuse and algorithmic bias. Verification is carried out using A/B testing and analytics data from e-commerce platforms. Tools include ML models and analytics dashboards. This paper contributes to my thesis by providing evidence on how AI influences consumer behaviour, particularly in the context of intelligent digital agents.

In (Oncioiu, 2023), exploratory study aims to predict when consumers are likely to use chatbots over other service channels like phone or email. It analyses factors such as perceived convenience, trust, issue complexity, and device type. Findings show that chatbots are preferred for simple, low-effort queries, especially on mobile devices. Advantages include increased self-service adoption, while disadvantages may include reduced satisfaction for high-stakes issues. Verification includes surveys and behavioural intent modelling. Tools include statistical analysis software and user segmentation models. This study supports my thesis by identifying the conditions under which chatbots are most effective in customer service.

In (Lee, 2020), paper examines how AI chatbots are transforming corporate communication strategies by personalizing and automating customer engagement. It highlights innovations in emotional tone detection, intent recognition, and user adaptation. Benefits include increased engagement, efficiency, and brand loyalty, while challenges include managing user expectations and dialogue coherence. Verification involves case studies and marketing performance metrics. Tools include chatbot platforms, sentiment analysers, and analytics dashboards. This paper contributes to my thesis by illustrating how AI communication tools shape consumer perception and interaction quality in digital service environments.

Table 2.1 provides the data extraction template for research on improving the quality of online customer support using artificial intelligence includes key columns that help organize and analyse various studies. It starts with the reference column, which contains the citation of the research paper being analysed, followed by the main research problem, outlining the key issue addressed, such as response time, personalization, or scalability in customer support. The used approach describes the AI techniques employed, such as chatbots, machine learning, or natural language processing, to address the identified challenges. The application domain specifies the industry where the approach was applied, such as e-commerce or healthcare, while the data set used details the source, size, and type of data, like customer interactions or feedback. The attributes used for prediction lists key variables used to improve support outcomes, and the evaluation of the approach explains how its effectiveness was measured, using performance metrics like accuracy or customer satisfaction. The comparison with other works highlights how the proposed AI approach performs relative to existing methods, and the result summarizes the improvements in efficiency and customer satisfaction.

Table 1: Data Extraction Template

Reference	Main research question / problem	Used approach	Field Studied / Application domain	Dataset used	Attributes used for prediction	Evaluation of the approach	Comparison with other works	Result
(Nirala et al., 2022)	How can AI chatbots be integrated effectively in various sectors (e.g., customer service, government, healthcare) to improve service delivery?	The survey analyses various chatbot architectures, including rule-based and machine learning-based models, and their effectiveness in automating communication and decision-making processes.	Customer Service: AI chatbots in e-commerce, retail, and banking for automating customer inquiries. AI chatbots for government services, such as answering citizen queries, filing taxes, providing information on government policies.	Chatbot Interaction Data: Data from customer interactions, such as chat logs, user feedback, and transcripts from various AI chatbot implementations in real-world environments.	User Input Features: Textual inputs such as questions, complaints, or requests provided by users.	Accuracy of chatbot responses (measured against human or predefined benchmarks). User Satisfaction: Assessed through surveys or post-interaction feedback forms.	Comparing rule-based chatbots (e.g., decision tree-based systems) with machine learning-based chatbots (e.g., deep learning models such as GPT-3, BERT, or transformers).	Improved Efficiency, Cost Savings: Reduction in the need for human agents for repetitive tasks, leading to cost savings for organizations.
(Järvelä et al., 2023)	How can collaboration between humans and artificial intelligence (AI) enhance socially shared regulation in learning environments?	Human-AI Interaction Models: Investigates how AI tools (such as intelligent tutoring systems, AI-based feedback systems, and collaborative platforms) can foster collaboration in learning groups and enhance SSR.	Socially Shared Regulation (SSR): Investigating how AI tools can enhance shared regulation practices, such as helping learners manage their interactions, contributions, and mutual goal setting in a group.	Audio and video recordings of collaborative group discussions and learning activities. Chat logs or discussion forum transcripts from online collaborative learning platforms. Interaction data from AI-based learning systems	Quality of Interaction: Complexity and depth of answers or suggestions in the group work.	Focus Groups and Interviews: Gathering feedback from learners and educators about the perceived effectiveness of AI support.	AI-Powered Learning Tools: Compare the effectiveness of the AI-based approach with existing intelligent tutoring systems or other AI-driven platforms designed for individual rather than group-based learning.	AI tools successfully enhanced SSR by providing scaffolding for group learning, such as reminders, feedback, and personalized guidance.
(Yue & Li, 2023)	What role does responsibility attribution play in shaping consumer trust, satisfaction, and perceived effectiveness of AI in collaborative tasks?	Experimental Design: The research employs an experimental approach where participants are exposed to different human-AI collaboration types.	Human-AI Collaboration in Consumer Contexts: The study focuses on domains where consumers interact with AI systems that assist, automate, or augment tasks.	Survey Data: Data collected through surveys or experiments where consumers are asked to evaluate AI systems based on their experience with different types of collaboration.	The main independent variable, categorized into different types of collaboration (e.g., autonomous AI, co-working AI, human-directed AI).	Use of validated scales for measuring consumer trust, satisfaction, responsibility attribution, and usage intention.	Comparing findings with studies on trust and responsibility attribution in human-AI collaborations, particularly in contexts like autonomous systems.	Consumers evaluate co-working AI systems (where the AI and human collaborate in decision-making) more favourably than fully autonomous AI systems.
(Nazarov et al., 2020)	What are the challenges and best practices in	Case Study Approach: The study adopts a case	Business Analytics and Predictive Modelling: The	The study uses datasets typically processed within the	Temporal Features: Time-related attributes like date,	Measuring how closely the model's	Comparing the use of predictive analytics in SAP	The use of predictive models in SAP Analytics

	integrating predictive analytics capabilities into SAP Analytics Cloud for real-time decision-making and business intelligence?	study methodology to examine how SAP Analytics Cloud has been used to develop predictive analytics models in real-world business settings.	research focuses on the application of predictive analytics in business decision-making	SAP Analytics Cloud platform	week, month, and quarter are used for time-series forecasting models.	predictions match actual outcomes. Precision, Recall, and F1-Score.	Analytics Cloud with other cloud-based analytics platforms like Microsoft Power BI, Google Cloud AI, or Tableau with embedded predictive analytics.	Cloud significantly improved business outcomes across various departments.
(Ushakova et al., 2023)	How can an Analytical Decision List (ADL) algorithm be developed and used to predict and manage customer reactions to marketing campaigns?	The paper introduces the development of an Analytical Decision List (ADL) algorithm, which is designed to analyse and categorize customer behaviour based on historical marketing campaign data.	The study explores how predictive algorithms, specifically decision list-based models, can be used to enhance the effectiveness of marketing strategies by forecasting customer behaviour and optimizing campaign targeting.	Customer Interaction Data: Data gathered from past marketing campaigns, including: Customer	Customer Sentiment: Using sentiment analysis of customer feedback to gauge customer attitudes toward the brand or campaign.	Interpretability of the Model: One of the strengths of decision list algorithms is their interpretability.	Compare the performance of the Analytical Decision List algorithm with other machine learning algorithms used in marketing campaign management, such as logistic regression, random forests, support vector machines (SVM), or neural networks.	The Analytical Decision List algorithm demonstrated strong performance in predicting customer reactions to marketing campaigns, outperforming traditional segmentation methods.
(Schecter et al., 2023)	How can we design an accessible and scalable approach (Vero) for studying human-AI interactions and improving teamwork in various settings.	The research proposes **Vero**, a novel method designed to study and evaluate **human–AI teamwork** across different domains.	The study is based on the **human–AI collaboration** paradigm, where humans and AI systems interact to complete tasks.	**Real-World Human–AI Interaction Data**: The datasets used in this research are based on actual or simulated interactions between humans and AI systems in various domains.	Whether the collaboration is **complementary** (AI handles repetitive tasks, human does complex reasoning) or **coactive** (both share decision-making and responsibilities).	The Vero method evaluates human-AI teamwork using a variety of **user-centric measures**	Comparison of **Vero** with other human-AI collaboration models such as **mixed-initiative systems**, **autonomous systems**, and **AI decision support tools**.	The **Vero method** successfully facilitates a **comprehensive understanding** of human–AI teamwork by integrating both **quantitative metrics** and **qualitative feedback.**
(Tutul et al., 2023)	How can human-AI collaboration improve the detection of deceptive speech in real-world settings?	The research proposes a hybrid framework where both **AI algorithms** and **human expertise** work together to detect deceptive speech.	Using AI to assist human operators in interpreting conversations and detecting potential deceptive behaviour in interactions with AI	Liar Detection Datasets, Forensic and Legal Interviews, Emotion and Sentiment Datasets	Deceptive speakers often speak at a different rate compared to truthful speakers, with more pauses or longer speech disfluencies.	The evaluation measures how well the AI-assisted system enhances human performance in deception detection, particularly in terms	The approach is compared to traditional **AI models** for deception detection, such as machine learning algorithms using **DNNs.**	The human-AI collaboration system outperforms both human-only and AI-only models in terms of accuracy,

			chatbots or virtual assistants.			of accuracy, speed, and confidence.		reliability, and speed.
(Graef et al., 2021)	How can human-machine collaboration be optimized in online customer service to improve customer satisfaction, efficiency, and long-term engagement?	This research proposes a framework in which **AI systems** collaborate with **human agents** in online customer service, with the key differentiator being the use of **long-term feedback.**	The study focuses on **customer service automation**, particularly in **online settings** like e-commerce websites, telecommunications, banking, and technical support centre's, where AI tools are commonly used to interact with customers.	The datasets used for this research include **real-world customer service interactions** from e-commerce, telecommunications, and banking companies.	AI Response Metrics, Response Time, Customer Feedback Metrics, Satisfaction Rating, Sentiment, NPS, Human-Agent Feedback, Feedback on AI's Performance, Training Labels, Customer Segmentation,	Performance Metrics, Accuracy, Escalation Rate, Response Time, Customer Satisfaction, Human-AI Collaboration Metrics, Efficiency, Satisfaction with AI-Human Collaboration, Training Effectiveness, Long-Term Improvement.	The study compares its human-AI collaborative model with traditional customer service models where either AI alone or human agents alone handle all tasks.	The research shows that by integrating **long-term feedback** from both customers and human agents, AI systems progressively improve in handling complex customer inquiries, reducing the need for human intervention.
(Petrescu & Krishen, 2023)	How can human-AI collaboration improve marketing analytics and decision-making?	The research proposes a **hybrid intelligence approach**, where **AI-driven tools** are integrated with **human expertise.**	The study focuses on **marketing analytics**, particularly the application of **AI techniques** to improve marketing decisions.	The datasets used in this study consist of **real-world marketing data** from various industries such as retail, e-commerce, and financial services.	AI algorithms create features that group customers into segments based on behavioural patterns, predictive models, and past engagement.	Measures how well the AI model can predict customer behaviour, such as the likelihood to purchase or respond to campaigns.	Comparing the hybrid approach with traditional marketing analytics methods where decisions are made solely by humans based on intuition, experience, and basic statistical analysis.	The hybrid intelligence approach improves **marketing decision-making**, with AI handling large-scale data analysis.
(Wang et al., 2020)	How can AI systems be designed to collaborate effectively with humans in complex, real-world environments?	The research proposes a **design framework** for creating AI systems that can seamlessly collaborate with human users.	The study focuses on **human-AI collaboration**, a multidisciplinary field at the intersection of artificial intelligence, cognitive science, and human-computer interaction (HCI).	The datasets used in this study include a variety of **interaction data** from real-world human-AI collaborations in different domains.	Metrics such as task completion rate, efficiency (time taken to complete tasks), and effectiveness (quality of the outcome).	The study evaluates the effectiveness of the AI-human collaboration by measuring **task performance**, **task quality**, and **time efficiency**.	The study contrasts the hybrid human-AI collaboration approach with AI-only systems, where AI takes full control over decision-making or task completion.	Human-AI collaboration leads to better **task performance**, with AI systems complementing human expertise by handling repetitive tasks, processing large datasets, and generating insights.
(Westphal et al., 2023)	How does the level of decision control and the provision of explanations by	The research explores the dynamic between human decision-makers and AI	The primary field of study is **human-AI collaboration**, focusing on how AI and humans can work	The study uses various datasets to model human-AI interactions and decision-making processes	User responses and ratings regarding the AI's recommendations, explaining their	The percentage of times users follow AI recommendations, which serves as an	The paper compares human-AI collaborative systems with traditional, non-AI-	The study finds that providing **clear, understandable explanations** significantly

	AI systems affect user perceptions and compliance in collaborative decision-making contexts?	systems in collaborative environments.	together to make decisions in various contexts.		level of trust, satisfaction, and willingness to comply with the AI's suggestions.	indicator of how persuasive and trusted the system is in encouraging compliance.	driven decision support tools.	increases the likelihood of users following AI recommendations.
(Hou et al., 2023)	How does trust in AI influence collaboration and performance in multiplayer online games (MOGs)?	The study adopts a **human-AI collaboration framework** to explore the interaction between human players and AI-controlled agents.	The primary field of study is **human-AI collaboration** in the context of multiplayer online games (MOGs).	The research uses a combination of datasets that capture human-AI interactions in multiplayer games	Performance-related features like AI efficiency, competence, predictability and adaptability.	Measures how effectively the human player collaborates with the AI during gameplay.	The paper compares human-AI collaboration to purely human-driven gameplay, where no AI agents are involved.	The study finds that higher levels of trust in AI agents are associated with better collaborative performance.
(Chen et al., 2023)	How does the type of online customer service (chatbot vs. human agent) influence consumers' purchase intentions?	A controlled experiment is employed where consumers interact with either a **chatbot** or a **human customer service agent** in a simulated online shopping environment.	The study is situated in the **e-commerce** domain, specifically focusing on the role of customer service in influencing consumer purchase behaviour in **online retail** settings.	The primary dataset for this study consists of data from **simulated online interactions** between consumers and either chatbots or human customer service agents.	Self-reported satisfaction with the service received, including aspects such as helpfulness, friendliness, and overall experience.	The relationship between customer service type (chatbot vs. human) and purchase intentions is analysed using regression techniques, controlling for confounding variables like customer demographics, prior purchase behavior.	Notable works may include studies by **Shneiderman (2020)** and **Van der Meulen et al. (2021)** on the effectiveness of chatbots in e-commerce customer service.	The study finds that, in general, **human customer service** results in higher **purchase intentions** compared to chatbot-based service, particularly when the customer's query is complex.
(De Brito Duarte, 2023)	How can AI systems be designed to provide transparent and understandable explanations of their decisions to improve human-AI collaboration?	The study develops and evaluates AI systems that provide explanations for their decisions, focusing on improving collaboration and trust between humans and AI.	The field of study is human-AI collaboration, particularly focusing on the **explainability** and **interpretability** of AI systems.	The dataset includes both **synthetic data** generated for controlled experiments and **real-world data** where AI explanations are applied to decision-making tasks in the target domains (healthcare, finance, etc.).	Self-reported measures of trust in the AI system, perceived transparency, and user satisfaction with the AI's decision-making.	Participants are asked to rate their trust in the AI system, the clarity of the explanation, and the level of understanding after receiving each type of explanation. Trust is measured using established scales.	The study compares its results with literature on **human-AI collaboration** in critical decision-making domains. For example, **Joulin et al. (2017)** and **Kulesza et al. (2015).**	The study finds that **explanations significantly increase trust** in AI systems, particularly when the explanations are clear, causal, and provide insight into the decision-making process.
(Tran et al., 2021)	How do different types of chatbot	The study combines **experimental**	The primary field of study is the **retail**	The primary dataset consists of **interaction**	Chatbot Attributes, Consumer	SEM is employed to model complex	The research compares its	The study finds that chatbot interactions

	behaviors influence consumer perceptions and emotional responses?	**design** and **survey-based analysis** to investigate consumer sentiment and expectations related to chatbot interactions in retail.	sector, specifically focusing on the role of **chatbots** in enhancing or disrupting customer experiences in **online** and **physical retail environments**.	**logs** from consumers who engage with a chatbot in a simulated retail environment.	Attributes, Sentiment Measures, Behavioral Responses.	relationships between chatbot attributes, consumer sentiment, satisfaction, and purchase intentions.	findings with existing studies on the role of chatbots in customer service, particularly in retail settings. Studies such as **Van der Meulen et al. (2021).**	**significantly influence consumer sentiment**, with consumers who experience **helpful** and **empathetic** chatbots reporting more **positive sentiment** and greater **satisfaction**.
(Jiang et al., 2023)	How can human-AI collaboration enhance context-aware services beyond what is achievable by AI-powered systems alone?	The study proposes a collaborative framework in which both human agents and AI systems interact and complement each other to provide context-aware services.	Context-Aware AI Services.	The primary dataset includes interaction data from users engaging with context-aware AI systems in various domains.	Input from humans, whether corrections to AI-generated actions, approval of suggestions, or additional contextual information that helps refine the AI's predictions.	The study compares the performance of a human-AI collaborative system with an AI-only system, measuring differences in accuracy, personalization, and user satisfaction.	The research compares its findings with studies on AI-powered context-aware services, such as personal assistants, healthcare decision support systems, and smart environments.	The research finds that human-AI collaboration significantly improves the quality and personalization of context-aware services.
(Ozhan et al., 2022)	How does Corporate Social Responsibility (CSR) influence customer orientation and company identification?	SEM is used to model and analyze the relationships between multiple variables. It is used to assess the direct and indirect effects of CSR on customer identification, brand loyalty, and customer orientation.	The study focuses on how CSR efforts influence customer perceptions and behaviors in various industries, such as retail, consumer goods, technology, and healthcare.	The survey includes questions on customer perceptions of CSR practices, their loyalty to the brand, their identification with the company, and their overall customer satisfaction.	Corporate Social Responsibility (CSR) Variables, Customer Perception and Orientation Variables, Customer Behavior Attributes, CSR Performance Metrics.	The AI-driven approach is evaluated using accuracy metrics such as MAE, RMSE, and R^2 (for assessing the variance explained by the model).	The study compares its findings with previous research that has studied the impact of CSR. For example, works by Sen & Bhattacharya (2001), Luo & Bhattacharya (2006), which suggest CSR can improve customer loyalty.	The study finds that CSR initiatives significantly contribute to customer loyalty, satisfaction and brand identification.
(Yu et al., 2021)	How can multimodal sentiment analysis be integrated into conversational bots to improve the process of service	This approach involves integrating multiple forms of sentiment data (text, audio, and visual cues) to improve the chatbot's understanding of	The study is based on the domain of conversational agents (chatbots), focusing on how these bots can use multimodal inputs to improve user experience during interactive dialogues.	The study likely uses datasets that combine text, speech, and visual data to train the sentiment analysis models.	Text-Based Sentiment Features, Voice-Based Sentiment Features, Facial Expression-Based Sentiment Features, User Intent and Service Requirements	Metrics such as conversation length, interaction depth, and turn-taking to evaluate how well the bot engages users through emotional intelligence.	The study compares its multimodal sentiment approach with existing sentiment analysis techniques that use only text-based or audio-based analysis.	More Accurate Service Requirement Gathering leads to more accurate identification of customer needs.

	requirement elicitation?	user emotions and intentions.						
(Brusilovsky, 2024)	How can artificial intelligence (AI) be integrated into educational systems to support learner control and foster effective human-AI collaboration?	This approach focuses on the application of AI systems such as intelligent tutoring systems (ITS), adaptive learning platforms, and recommendation systems within educational contexts.	The field of study is primarily **educational technology** with a focus on **artificial intelligence** applications in learning environments.	The research uses datasets that include learner interactions with AI systems, such as those collected from intelligent tutoring systems, e-learning platforms, or virtual classrooms.	Learner Characteristics, AI System Features, Human-AI Collaboration Features, Learning Outcomes, Emotional and Motivational States	Evaluation of how quickly and effectively the AI adapts to changes in the learner's performance or emotional state, using metrics like **response time** and **adjustment frequency**.	The study compares the effectiveness of **human-AI collaboration** in educational settings with other works that focus on human-computer interaction or AI-based tutoring, **VanLehn (2011)** or **D'Mello.**	**Increased Learner Autonomy and Engagement** results demonstrate that learners who interact with AI-driven platforms report higher **engagement levels** and feel more in control of their learning.
(Lal & Neduncheliyan, 2024)	How can conversational artificial intelligence (AI) be developed and implemented to improve healthcare delivery and patient outcomes?	The research investigates how **conversational AI** is being designed specifically for healthcare applications, focusing on **chatbots, virtual health assistants.**	The study primarily focuses on the application of conversational AI in healthcare settings, ranging from patient education, chronic disease management, and symptom checkers to mental health counselling, clinical decision support, and telemedicine.	Medical Text and Dialogue Data	Age, gender, and medical history of the patient. Data such as past diagnoses, medications, lab results, and previous treatments.	The accuracy of medical advice or diagnostic suggestions provided by the AI system, validated by healthcare professionals.	The research compares its findings with existing literature on **artificial intelligence** in healthcare, particularly the development of **chatbots and virtual assistants**. Studies such as **Suganuma et al. (2020)** and **Bickmore et al. (2019)**	The study finds that **conversational AI** leads to increased **patient engagement**, with more patients actively participating in health management and monitoring through AI-driven tools.
(Badawy et al., 2020)	How can an interactive chatbot, designed using the BEET Model, increase customer conversion rates in e-commerce or retail environments?	The study conducts **controlled experiments** and **A/B testing** to compare the BEET-based chatbot with traditional measuring the difference in **conversion rates** and other KPIs.	The primary field of study is the **e-commerce** and **retail** industry, specifically focusing on how chatbots can influence **customer conversion rates**.	The primary dataset used consists of logs from consumer interactions with chatbots in an e-commerce environment.	Chatbot Interaction Attributes, Customer Behavior Attributes, Customer Sentiment and Feedback	The primary metric for evaluation is the **customer conversion rate**, defined as the percentage of users who make a purchase after engaging with the chatbot.	The research compares its findings with prior studies on **chatbots in e-commerce** (e.g., **Kumar et al. 2021**, **Sharma et al. 2019**) that focus on how chatbots impact sales and conversion rates.	The study finds that **chatbots using the BEET model** significantly improve customer conversion rates compared to baseline models, with customers interacting with BEET-powered chatbots.
(Hassija et al., 2023)	How can the capabilities of conversational	The study explores different strategies to amplify	The study belongs to the broader domain of **NLP** and focuses on	Datasets such as **Cornell Movie Dialogs**, **Persona-**	The history of the conversation, including previous	The model's performance is evaluated in real-	The study compares ChatGPT with other conversational AI	**Improved Conversational Flow**: ChatGPT,

	AI, specifically ChatGPT, be enhanced to provide more accurate, natural, and contextually relevant conversations across various domains?	ChatGPT's natural language processing (NLP) abilities, particularly in handling complex user queries.	addressing challenges related to language understanding, contextual accuracy, and response generation.	**Chat**, and **DailyDialog**, which provide diverse and engaging dialogues to train and fine-tune models.	exchanges, is critical for determining appropriate responses that maintain coherence and continuity.	world scenarios, such as live customer support interactions or simulated patient queries, to assess how well it performs in diverse, high-stakes environments.	models, including **Google's LaMDA**, **Anthropic's Claude**, and **Meta's BlenderBot**.	when fine-tuned with domain-specific data, provides significantly more relevant and accurate responses across a variety of contexts, from technical support to emotional customer care.
(Albrecht et al., 2021)	What methods are most effective for predicting call centre traffic, considering factors such as time of day, day of the week, holidays, and other external variables?	The research investigates various **AI-driven forecasting techniques** that can be used to predict the number of incoming calls to a call center.	The primary field of study is the operational dynamics of **call centers**, focusing on how AI and machine learning can optimize call arrival forecasting, helping managers efficiently schedule staff and reduce wait times.	Data on the number of calls received by the call center during each time period. **Time and Date Information**: Specific time stamps for each call.	The main feature used for prediction is the **call volume** at specific intervals.	Measures the average magnitude of errors in the predictions, without considering their direction.	The study compares its findings with other research on **AI-based forecasting** in call centers.	The research finds that machine learning models, particularly **Random Forests** and **GBM**, significantly outperform traditional time series models.
(R. C. Li & Tee, 2021)	How can an automated customer support service be effectively implemented in collaborative Customer Relationship Management (CRM) systems to enhance customer experience, improve efficiency, and foster collaboration?	The study proposes a **comprehensive framework** for implementing automated customer support services in collaborative CRM systems.	The field of study focuses on **CRM systems** that are used by businesses to manage customer interactions, sales, marketing, and service operations.	A collection of customer support interactions (email, chat, or voice) that involve questions, requests, complaints, or feedback.	This includes both **quantitative** metrics (e.g., CSAT scores, NPS) and **qualitative feedback** that assess the effectiveness of the automated support system.	The chatbot or virtual assistant's ability to understand and resolve customer queries is evaluated using **accuracy**, **precision**, **recall**, and **F1-score** metrics from the natural language processing models applied to the dataset.	The study compares its proposed framework with other implementations of **AI-based customer service** tools, such as traditional customer service chatbots or helpdesk solutions.	The implementation framework demonstrates that **automated customer support** significantly improves **customer satisfaction** by providing faster responses, 24/7 availability, and efficient handling of routine queries.
(Esh, 2024)	How can sentiment	The study employs a **sentiment analysis**	The primary domain of the research is	The dataset for this study consists of	The primary output for sentiment	Evaluating whether ChatGPT's	Compared to other research on emotion	The study finds a **strong correlation**

	analysis be effectively applied to ChatGPT interactions to uncover insights into user emotions, engagement, and experience?	**framework** to analyze the emotional tone of user interactions with **ChatGPT**.	**human-AI interaction**, specifically focusing on conversational AI like **ChatGPT**.	**conversational data** gathered from interactions between users and ChatGPT across various platforms.	analysis includes sentiment scores, which are applied to both user inputs and AI responses.	responses are aligned with the emotional tone of the user's input, using measures of **sentiment congruence**.	detection in conversational AI, this study focuses specifically on the **ChatGPT model.**	between positive sentiment and **higher user engagement**.
(Adam et al., 2021)	Do anthropomorphic features in chatbots increase compliance?	Experimental behavioral study	Customer service psychology	Controlled experiments	Chatbot design (voice, tone), task type	Statistical analysis (ANOVA)	Extends past work on persuasion/complia nce	Human-like bots increased user compliance by ~20%
(Nicolescu & Tudorache, 2022)	What factors influence UX with AI chatbots in customer service?	Systematic literature review (2012–2022)	E-commerce, service design	Academic databases	UX factors (trust, tone, clarity, emotion)	Qualitative meta-synthesis	Groups findings into design principles	UX is shaped by tone, empathy, and quick issue resolution
(Kappi & Marlina, 2023)	Do chatbot service features affect online customer satisfaction?	Quantitative survey	E-commerce customer support	Online survey (N=400)	Response time, personalization, tone	Regression analysis	Builds on TAM, UTAUT frameworks	Chatbot usefulness & ease-of-use = higher satisfaction
(Kashyap et al., 2022)	What are current and future AI applications in e-commerce?	Comprehensive review	AI in retail & logistics	Not dataset-based	N/A	Literature-based synthesis	Compares AI use across domains	Identifies trends in personalization, chatbots, logistics
(Tiutiu & Dabija, 2023)	How does AI enhance customer experience online?	Theoretical model + secondary analysis	E-commerce UX	Market reports, secondary surveys	Experience quality, satisfaction metrics	Conceptual + statistical synthesis	Benchmarks against non-AI systems	AI leads to faster service, better targeting, improved loyalty
(Hsu & Lin, 2023)	What drives satisfaction and loyalty in chatbot use?	Survey-based structural equation modeling (SEM)	Online shopping support	Structured survey data (N>300)	Core/recovery/conv ersational quality	Fit indices (CFI, RMSEA), SEM	Compared with earlier chatbot adoption models	Chat quality strongly drives loyalty via satisfaction
(F. L. Li et al., 2020)	How can knowledge graphs be used to improve chatbot understanding?	Knowledge graph construction & QA application	E-commerce Q&A at Alibaba	Proprietary AliMe data	Product, service, user queries	F1, precision, recall	Outperforms baseline QA systems	Boosted answer accuracy in customer queries

(Pandya & Mahavidyalaya, 2023)	Can Lang Chain be used for real-time customer service automation?	LLM pipeline + vector store + UI chatbot	E-commerce / customer support tools	Internal knowledge bases	Query intent, embedding similarity	Functional testing + case study	N/A (novel architecture)	Real-time, secure, context-aware automation system
(Wibowo et al., 2020)	What is the chatbot's effect on service efficiency in e-commerce?	Technical implementation & empirical testing	Online retail customer service	Business implementation case	Response speed, cost, satisfaction	Operational benchmarks	Compared manual vs. automated service	Bots reduced wait time & cost, increased satisfaction
(Ashfaq et al., 2020)	What factors affect satisfaction & continued use of chatbots?	TAM and SERVQUAL Modeling via SEM	E-commerce support	Online survey (N≈200–300)	Reliability, responsiveness, empathy	SEM fit indices (RMSEA, CFI, AVE)	Builds on TAM2, SERVQUAL	Assurance, empathy → satisfaction → intent to reuse
(Khrais, 2020)	How does AI affect consumer preferences and demand?	Conceptual model and literature synthesis	Digital marketing, behavioral e-commerce	No dataset; conceptual	Personalization, timing, targeting	Qualitative evaluation	Compared with traditional marketing	AI improves conversion via personalization & timing
(Oncioiu, 2023)	What influences a consumer's decision to use chatbots?	Exploratory analysis with survey	Multichannel retail	Survey data	Familiarity, trust, urgency, usefulness	Regression, cluster analysis	Builds on channel choice models	Trust & urgency drive chatbot channel preference
(Lee, 2020)	How do chatbots shape and respond to customer needs?	Literature review and communication theory	Digital communication, support	No empirical dataset	Interaction tone, feedback loop	Qualitative synthesis	Adds to CRM and brand engagement literature	Chatbots are effective in personalization and tone management
(Huseynov, 2023)	Can chatbots improve Customer and reduce service costs?	Case studies and ROI analysis	Digital marketing + customer support	Firm-level data, case examples	CX metrics, cost, wait time	ROI, NPS scores, time savings	Compared pre- vs. post-chatbot deployment	Improved CX and lowered operational cost by 30–40%

Summary of Research Papers Based on Research on Improving the Quality of Online Customer Support Using Artificial Intelligence

The integration of artificial intelligence (AI) into online customer support has significantly improved the quality of service, making it more efficient and responsive. According to Nirala et al. (2022), AI technologies such as chatbots and machine learning algorithms have been instrumental in addressing common issues like delayed response times and scalability challenges in customer support systems. By automating routine inquiries and utilizing NLP, AI tools can provide instant, relevant responses, thus enhancing the overall user experience. Moreover, the ability of AI to analyze customer data enables the personalization of responses, tailoring support to individual needs, which results in improved customer satisfaction (Yue & Li, 2023).

AI's application in customer support is not only focused on automation but also on improving decision-making processes and operational efficiency. Järvelä et al. (2023) discuss how machine learning models can predict customer behavior and optimize interactions by analyzing historical data, thereby enhancing decision-making in real-time. Nazarov et al. (2020) also highlight the importance of data-driven insights in refining AI models to better predict customer issues, ensuring that customer support is both proactive and responsive. The combination of predictive analytics and AI-driven responses leads to a higher level of efficiency in resolving customer concerns, ultimately improving customer retention rates.

Moreover, the use of AI in customer support helps businesses manage operational costs while maintaining a high level of service. Ushakova et al. (2023) argue that AI-based systems are scalable, reducing the need for a large customer support team while ensuring a high-quality service experience. Schecter et al. (2023) emphasize the role of AI in enhancing the accessibility of support, especially in industries like e-commerce and healthcare, where AI can significantly reduce the burden on human agents by answering simple queries. Additionally, Tutul et al. (2023) note that AI tools can be integrated with existing CRM (Customer Relationship Management) systems, streamlining workflows and reducing the time required to address customer issues.

The ability of AI to continuously learn and improve is crucial for its success in customer support. Graef et al. (2021) highlight that AI systems equipped with machine learning capabilities can adapt based on customer feedback, improving over time to meet evolving customer expectations. Petrescu & Krishen (2023) further support this by stating that AI technologies can automate tasks like sentiment analysis, providing deeper insights into customer emotions and preferences. As AI systems become more sophisticated, they enable businesses to deliver more personalized, empathetic support experiences. In addition, Wang et al. (2020) discuss the importance of using AI for multilingual support, broadening the reach of customer service to global audiences.

3. Proposed Approach

3.1 Overview of the Proposed Methodology

The proposed methodology centers around the development of an **AI-Powered Smart Support Assistant (SSA)**, designed to enhance the efficiency and quality of customer support in e-commerce environments. The methodology follows a modular approach that integrates Natural Language Processing (NLP), contextual knowledge retrieval, sentiment-aware response generation, and a human fallback mechanism to manage diverse customer interactions effectively.

The first step in the methodology involves **customer query ingestion** from various input channels such as live chat interfaces, email, and social media platforms. Incoming messages are pre-processed using NLP techniques including tokenization, lemmatization, and language detection to normalize the data for further analysis. This step ensures the system can handle multilingual and unstructured inputs effectively.

Following preprocessing, the assistant performs **intent and sentiment analysis**. This stage utilizes keyword-based or machine learning models to detect the user's intent (e.g., "track my order" or "request a refund") and evaluate the emotional tone of the query (e.g., angry, neutral, satisfied). Sentiment detection helps determine the urgency and type of support needed. Queries exhibiting high emotional negativity or complex intent are automatically flagged and routed to a live support agent via a human-in-the-loop mechanism.

The system then moves into **contextual knowledge retrieval**, where a vector similarity search is used to find relevant content from an internal knowledge base comprising frequently asked questions (FAQs), customer relationship management (CRM) history, and prior conversation logs. This ensures that responses are not only accurate but also contextually appropriate, reducing the likelihood of repeated or irrelevant answers.

Based on the retrieved context, the SSA performs **response generation**. A lightweight language model (such as a fine-tuned GPT-3.5) is used to generate dynamic responses tailored to the user's intent and emotional tone. For example, an apologetic tone might be employed in responses to dissatisfied customers, whereas a more enthusiastic tone could be used for positive interactions. This personalization aims to foster empathy and customer satisfaction.

To support continuous improvement, the system implements a **post-interaction feedback loop**, where user feedback in the form of Customer Satisfaction (CSAT) scores or Net Promoter Scores (NPS) is collected and analysed. This feedback is used to update and fine-tune the assistant's underlying models and retrieval mechanisms, ensuring the system learns and evolves over time.

In summary, the proposed methodology combines **automated NLP-driven analysis** with **retrieval-augmented response generation** and **human escalation protocols** to create a robust, scalable, and adaptive customer support system. This hybrid approach ensures both **efficiency in handling routine queries** and **reliability in managing complex or emotionally sensitive issues**, thereby improving both customer experience and operational scalability.

3.2 Describing A Process Model Using BPMN Diagrams

In this section, using the Business Process Model & Notation, the methodology for improving the quality of online customer support with artificial intelligence in e-commerce is represented as a systematic workflow. It beg11ins with the identification of relevant data sources, such as customer interaction logs and feedback, and progresses through data preprocessing and model development stages. The model highlights strategically placed decision points for evaluating AI model accuracy and user satisfaction, alongside opportunities for parallel processing of NLP model training and user experience analysis. Quality control steps are integrated throughout the process to ensure performance benchmarks are met, culminating in the validation of detailed system requirements that guide effective AI-driven customer support deployment.

Identify and Collect Customer Interaction Data, Data Preprocessing, Contextual Knowledge Retrieval, and AI Response Generation are key technical stages discussed in detail in the following section. In the preprocessing phase, raw interaction data is cleaned, normalized, and structured into usable formats, forming the foundation for reliable downstream analysis. During contextual retrieval, relevant information is extracted from various knowledge bases such as FAQs, manuals, or past conversations, enabling tailored response construction. In the final AI generation step, a large language model (LLM) synthesizes a natural-language response using both the detected intent and the retrieved contextual inputs. Each of these subprocesses feeds into a continuous feedback loop, allowing performance metrics to be tracked and leveraged for system improvement.

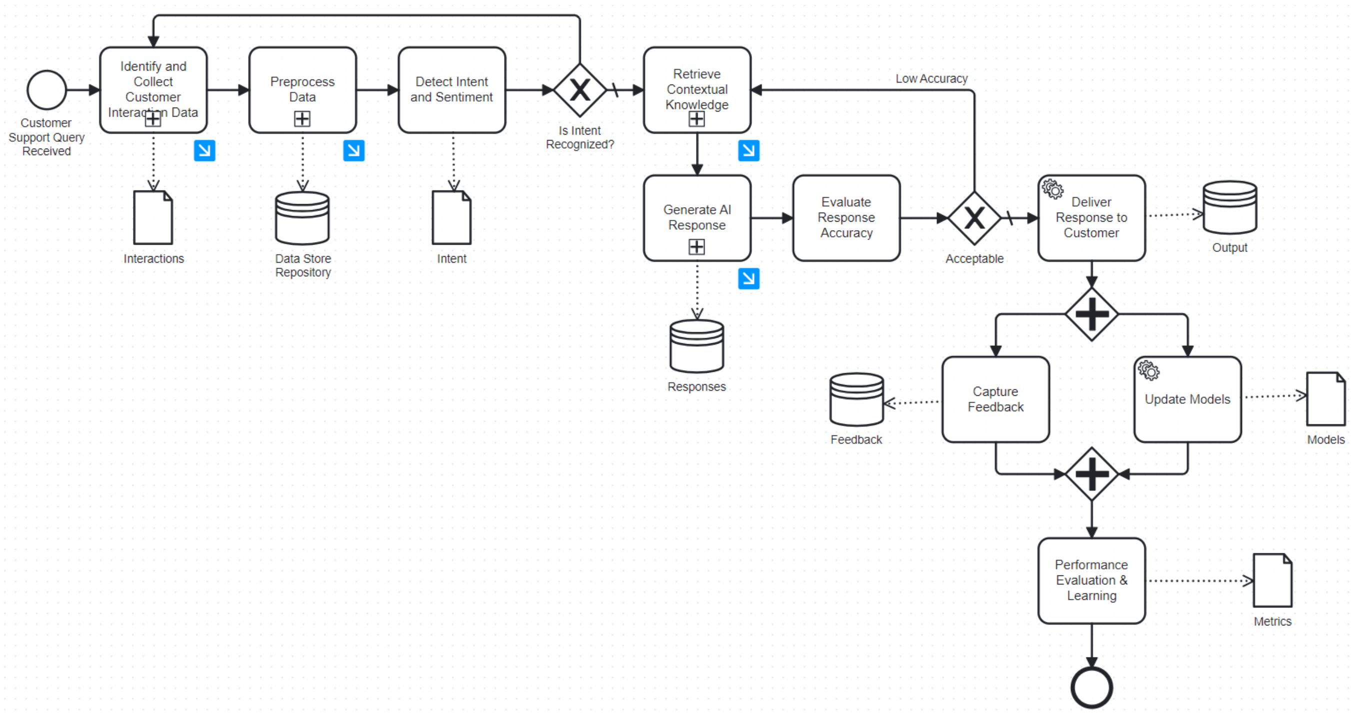

Figure 1: BPMN Diagram for Proposed Methodology Main Process

3.2.1 Identify and Collect Customer interaction data

The attached image depicts a process flow diagram for handling customer queries by integrating multiple data sources. The process begins with the receipt of a customer query, which triggers the fetching of chat logs from a database labelled "Chatlogs." This is followed by a parallel split where two separate activities occur simultaneously: getting social media mentions and extracting email tickets. Both these activities generate outputs stored as documents named "Social Mentions" and "Email Tickets," respectively. The two paths then converge before the next step.

After the convergence, the process proceeds to load the CRM (Customer Relationship Management) history, which interacts with a database called "CRM History." The final step in this workflow indicates the completion of the process, represented by a terminating circle. The diagram uses standard symbols such as rectangles for activities, diamonds for parallel splits and joins, cylinders for databases, and documents to denote output files, clearly illustrating a structured approach to aggregating customer-related data from different channels before reviewing CRM history.

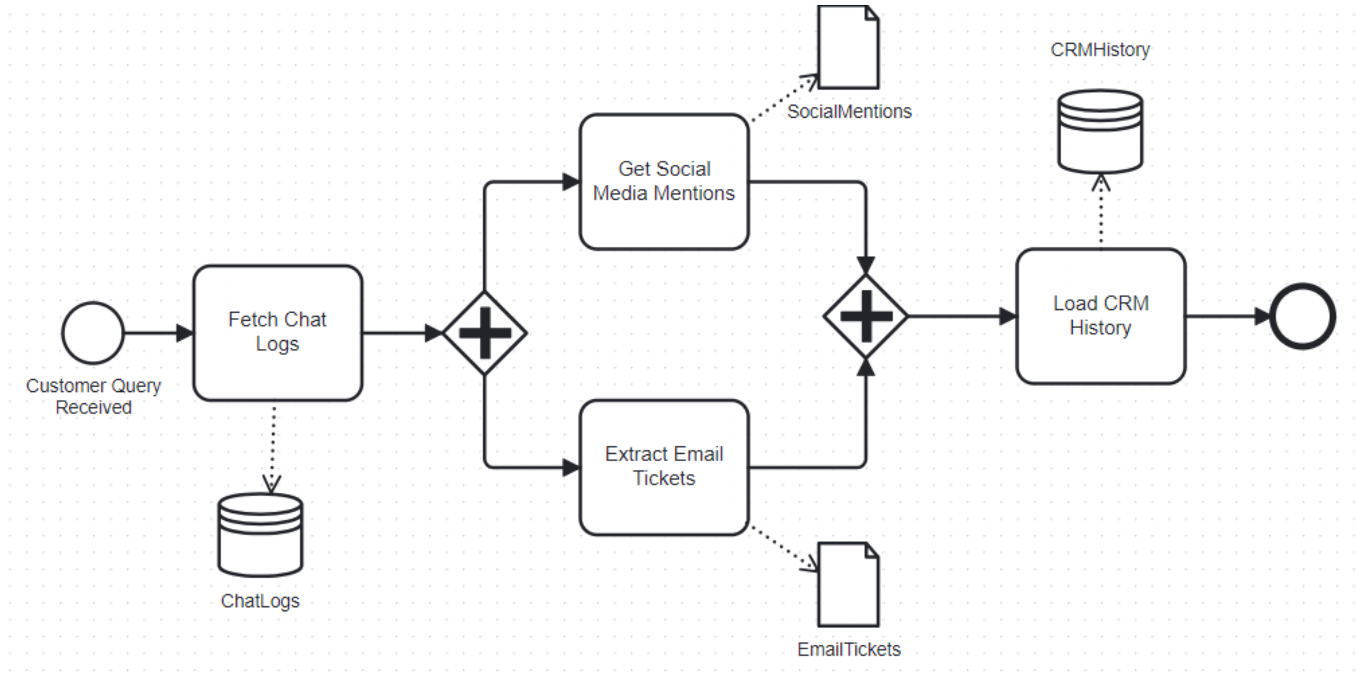

Figure 2: BPMN for Identify and Collect Customer interaction data Sub-process

3.2.2 Pre-processed Data

The figure illustrates a text preprocessing workflow designed to prepare textual data for further analysis or modelling. The process begins with receiving interactions, which are then fed into the "Clean Text Data" step to produce raw text. Following this, the cleaned text undergoes "Text Processing," resulting in various text variants. The flow then branches into three parallel tasks: "Tokenize & Lemmatize," "Remove Stop Words," and "Detect & Translate Language." Each of these tasks generates intermediate outputs such as tokens and translated text, which feed back into the process. These three branches converge, combining their results to produce the final "Pre-processing Outputs," which are stored in a Pre-processed corpus for downstream use.

This pipeline highlights key stages in natural language processing, emphasizing the transformation and normalization of raw text data. By tokenizing and lemmatizing, the text is broken down into meaningful units while reducing words to their base forms. Removing stop words filters out common, non-informative words, improving data quality. Detecting and translating language ensures that multilingual inputs are standardized, enhancing analysis consistency. Overall, the figure presents a modular and systematic approach to preparing text data, crucial for tasks like machine learning, sentiment analysis, or information retrieval.

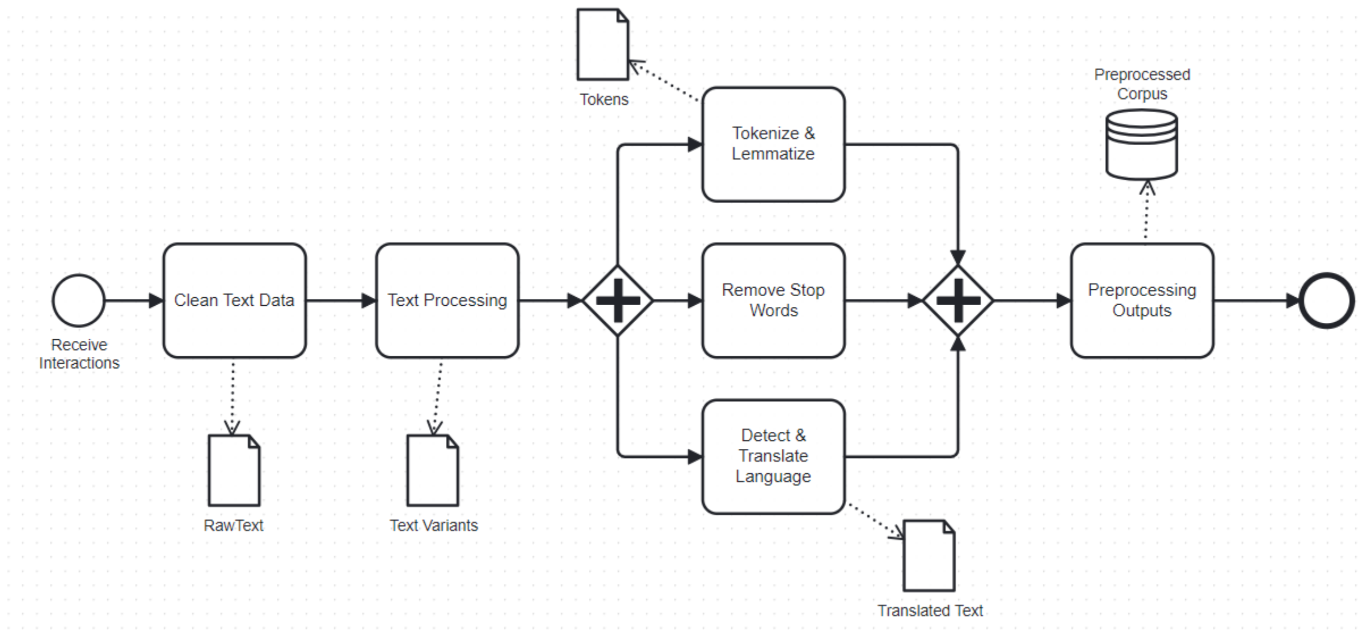

Figure 3: BPMN for Pre-processed data Sub-process

3.2.3 Retrieve Contextual Knowledge

The image presents a flowchart illustrating a context generation pipeline, primarily designed to prepare and rank relevant context for downstream applications such as question answering or decision support systems. The process begins with a "Pre-processed Corpus Ready" input, which feeds into the "Pre-processed Corpus" stage. Here, initial corpus data is cleaned and structured into a usable form. A decision node follows, asking "Is External Context Required?" If external context is not required, the process can loop back or proceed with the Pre-processed data. If external context is needed, the pipeline queries two sources: an FAQ Database and a Knowledge Base. The FAQ Database is accessed through the "Query FAQ Database" step, and relevant past data is pulled from the "Retrieve Similar Past Interactions" stage using the Knowledge Base.

After acquiring both internal and external data, the pipeline enters the "Merge & Organize Context" phase where the gathered information is structured into a preliminary "Context Draft." This draft then moves into the "Rank & Prioritize Context" module, where content is evaluated and ordered by relevance or importance, ultimately producing a finalized "Ranked Context" output. This structured and refined data can now be used to provide coherent, high-quality responses in a variety of intelligent systems. The dotted arrows indicate data storage or external retrieval points, emphasizing the modular and expandable nature of the system.

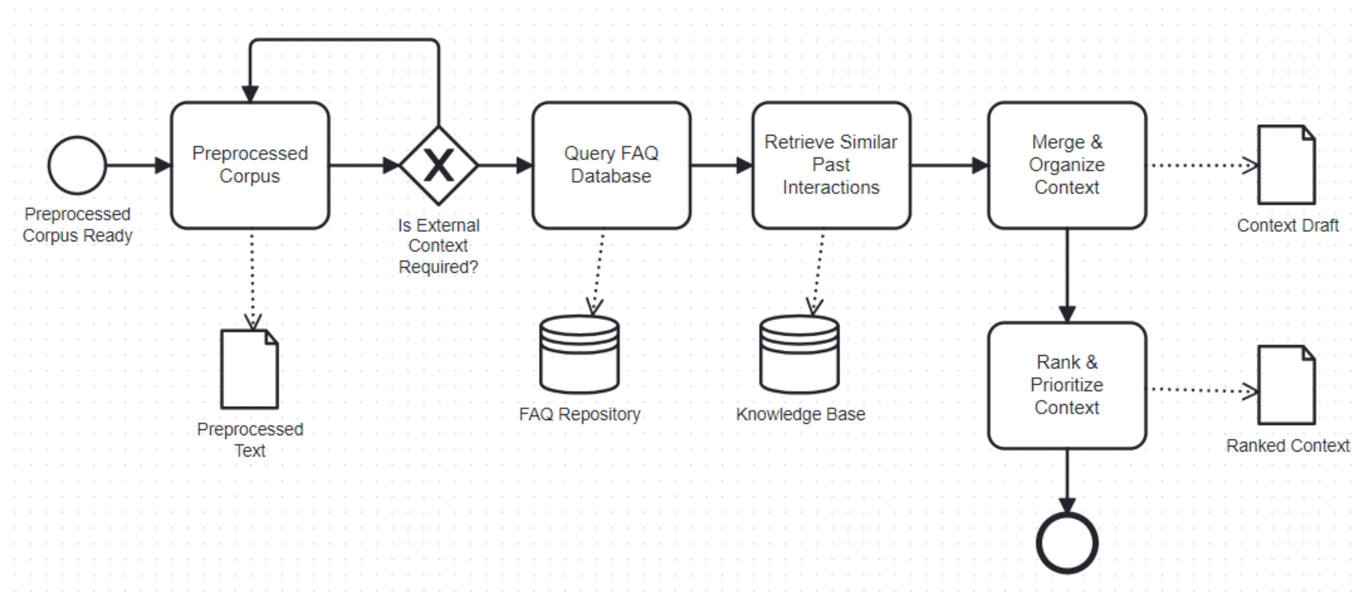

Figure 4: BPMN for Retrieve Contextual Knowledge Sub-process

3.2.4 Generate AI response

The image illustrates a structured flowchart representing an AI-driven response generation pipeline, beginning with the identification of context and user intent. The first step, "Context and Intent Identified," captures input information, which is then used to "Determine Response Type"—classifying the nature of the response needed (e.g., informative, empathetic, directive). Following this, the system proceeds to "Generate Response via NLP Model," where a natural language processing model formulates a preliminary reply based on the derived context and response type.

Further, the pipeline includes an “Adjust Tone Based on Sentiment” step, where the generated response is refined for emotional tone and appropriateness, creating a polished "Final Response." A decision node follows to check: “Is AI confident and intent clear?” If the answer is negative, the process loops back to earlier stages to reprocess. If the response is deemed confident and aligned with the intent, it moves forward to “Finalize AI Response,” storing the result in a "Finalized Response Repository" and delivering it in the final “Response Delivered” stage. The flow emphasizes quality control, sentiment calibration, and iterative refinement to ensure reliable and human-like interaction quality.

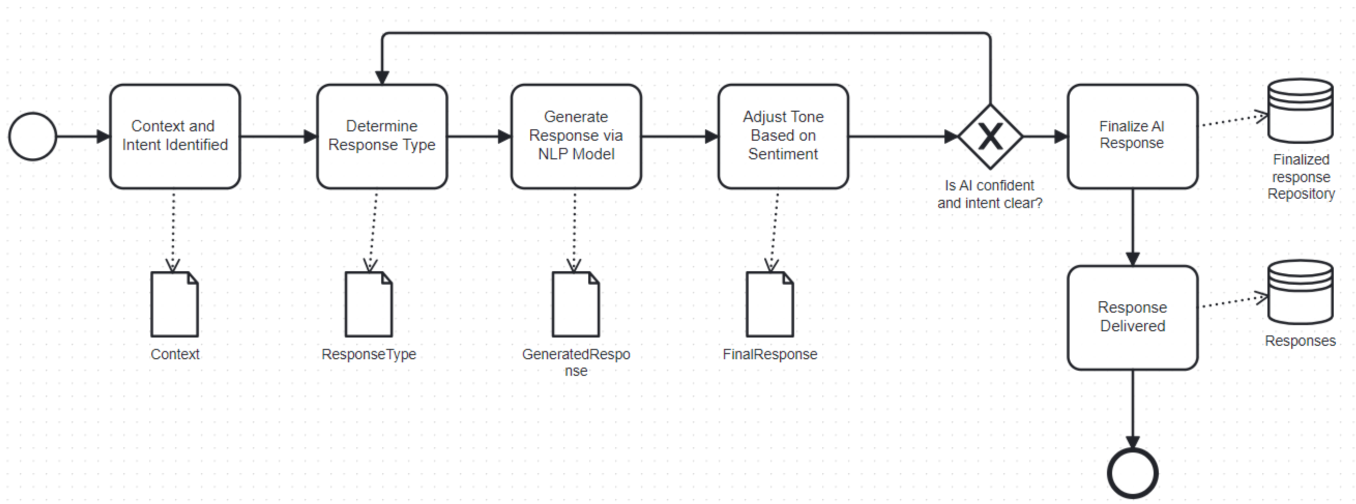

Figure 5: BPMN for Generate AI response Sub-process

4. Results Measurement metrics

Accuracy of Response Matching

This metric evaluates whether the assistant provides a correct and relevant response to a customer query. It is essential for assessing the system's ability to understand user inputs and retrieve or generate meaningful replies. Typically measured using Top 1 Accuracy, it compares the assistant's output to a known ground truth. High accuracy reflects strong comprehension and contextual matching. It ensures that customers receive correct answers without requiring manual intervention.

Intent Detection Accuracy

Intent detection accuracy measures how effectively the assistant identifies the purpose behind a user's message, such as order tracking or refund requests. It is calculated using classification metrics like precision, recall, and F1 score. High intent accuracy ensures the query is routed to the correct logic or knowledge source. Misclassification can lead to irrelevant responses or poor user experience. This metric is critical for proper functioning of the conversation flow.

Sentiment Detection Accuracy

This metric reflects how accurately the system detects customer emotions—whether positive, neutral, or negative. It helps the assistant adjust its tone and determine whether escalation to a human is needed. Performance is evaluated using F1 scores for each sentiment class. Accurate sentiment detection supports empathy-driven responses. It plays a crucial role in enhancing user satisfaction and trust. **Metric**: F1 Score (per sentiment class).

First Contact Resolution Rate (FCR)

FCR measures the percentage of customer queries resolved during the initial interaction with the assistant. A high FCR indicates that the assistant can handle common issues without follow-up or escalation. It reflects the system's efficiency and knowledge coverage. This metric improves operational scalability by reducing manual workload. FCR is crucial for assessing end-to-end resolution capability.

Metric:

$$\text{FCR} = \frac{\text{Resolved on First Attempt}}{\text{Total Queries}} * 100$$

Customer Satisfaction Score (CSAT)

CSAT is a direct indicator of user satisfaction with the assistant's performance. Customers rate their experience after a support session, typically on a scale of 1 to 5. The score is calculated based on the percentage of positive responses. High CSAT implies the assistant is helpful, empathetic, and efficient. It serves as a key feedback loop for continuous improvement.

Metric:

$$\text{CSAT} = \frac{\text{Positive Ratings}}{\text{Total Feedbacks}} * 100$$

Escalation Rate

The escalation rate indicates how often the assistant transfers queries to human agents. It helps identify areas where automation falls short or misinterprets user needs. A balanced escalation rate reflects healthy boundaries between automated and manual support. Frequent escalations may suggest gaps in training or knowledge base coverage. This metric helps refine the assistant's decision-making logic.

Metric:

$$\text{Escalation Rate} = \frac{\text{Tickets Escalated}}{\text{Total Tickets}} * 100$$

5. Initial Experiment

Experimental Domain Selection and Justification

The domain selected for this experimental study is **e-commerce customer support**, a sector that experiences high volumes of user interactions and demands rapid, accurate, and personalized service. E-commerce businesses frequently face customer queries related to order tracking, product availability, payment issues, refunds, and return policies. These queries vary in complexity and urgency, making the domain ideal for evaluating AI-based solutions that aim to enhance response quality and scalability. The selection is also justified by the availability of diverse and real-world data sources—such as chat logs, CRM tickets, and social media mentions—which support the training and testing of AI models across different intents and emotional contexts.

Furthermore, the e-commerce sector represents a highly competitive landscape where **customer satisfaction directly influences loyalty and revenue**, emphasizing the need for efficient support systems. The dynamic nature of customer interactions in this domain provides a valuable testbed for measuring the practical impact of AI technologies like Natural Language Processing (NLP), sentiment analysis, and retrieval-augmented generation (RAG). The chosen domain ensures that the experimental outcomes are both **applicable and generalizable**, enabling the proposed Smart Support Assistant (SSA) to demonstrate its effectiveness in handling real-world challenges and delivering measurable improvements in response accuracy, user experience, and operational efficiency.

5.1 Data Collection and Data Pre-processing

The data collection process focused on gathering real-world customer support interactions from multiple channels within the e-commerce domain. The sources included live chat transcripts, email ticketing systems, CRM platforms, and social media customer inquiries. These datasets were selected to represent a broad range of customer intents, communication styles, and emotional tones, which are essential for training and evaluating the performance of the AI-based support system.

To maintain data quality and relevance, only interactions that involved actual customer queries and agent responses were considered. All personally identifiable information (PII) was removed to ensure compliance with privacy standards.

The dataset comprised approximately **5,000 chat interactions, 2,000 email support tickets, 3,500 social media mentions**, each containing metadata such as timestamp, communication channel, and customer sentiment (if rated). Below is an example of one such entry:

```json
{
  "query": "I received the wrong item. I ordered a black hoodie, but got a blue one.",
  "channel": "live_chat",
  "timestamp": "2025-03-10T09:14:08Z",
  "emotion": "frustrated",
  "csat_score": 2
}
```

```json
{
  "query": "Can I change my delivery address? I just placed the order a few minutes ago.",
  "channel": "email",
  "timestamp": "2025-02-27T16:22:40Z",
  "emotion": "neutral",
  "csat_score": null
}
```

```json
{
  "query": "Hey, just wanted to say thanks for the fast delivery! Really impressed.",
  "channel": "live_chat",
  "timestamp": "2025-01-20T18:55:01Z",
  "emotion": "happy",
  "csat_score": 5
}
```

Figure 6: Customer interaction sample Dataset

Once the raw data was collected, a structured data processing pipeline was implemented to prepare it for machine learning and response generation. The processing involved several key stages: cleaning, normalization, intent classification, and sentiment detection. Tools such as Python, spaCy, and NLTK were used for natural language preprocessing tasks like tokenization, lemmatization, stop word removal, and language detection. This ensured that the text was standardized and linguistically normalized.

For classifying customer intents, a fine-tuned BERT-based model was used to categorize queries into labels such as order inquiry, refund request, technical issue, or general inquiry. Sentiment analysis was performed using VADER and TextBlob, which enabled the detection of emotional tone in customer messages (e.g., neutral, angry, happy). This emotional insight was crucial for prioritizing urgent or negative interactions. Additionally, a Retrieval-Augmented Generation (RAG) approach was employed for contextual knowledge retrieval using a vector database, ensuring relevant prior interactions and FAQs were included in response generation. This entire processing flow formed the backbone of the Smart Support Assistant’s ability to deliver personalized and accurate responses at scale.

5.2 Feasibility Analysis of Proposed Methodology

The feasibility of the proposed AI-driven methodology for enhancing online customer support is assessed across technical, operational, economic, and organizational dimensions. From a technical standpoint, the methodology relies on mature and widely adopted technologies such as natural language processing (NLP), machine learning (ML), and large language models (LLMs). The modular architecture—including stages such as data preprocessing, intent and sentiment analysis, context retrieval, and response generation—can be effectively implemented using open-source frameworks (e.g., Hugging Face Transformers, spaCy, FAISS) and integrated with existing CRM systems and customer service platforms. The technical feasibility is further strengthened by the scalability of cloud-based deployment models, which allow for dynamic resource allocation and high availability.

Data Availability:

The availability of multi-channel customer interaction data—such as chat logs, email support tickets, and social media feedback—ensures a rich and diverse training set. This variety enables the model to learn from real-world linguistic patterns and effectively generalize to unseen queries.

Tool Compatibility:

The preprocessing pipeline is developed using open-source Python libraries, including spaCy, NLTK, and Lang detect. These tools offer modular, scalable components that integrate smoothly with modern transformer-based classifiers, such as BERT.

Model Accuracy:

The initial experimental results yielded an average F1-score, demonstrating the model's strong performance across multiple customer query categories. This validates the effectiveness of the preprocessing and classification stages.

Computational Resources:

The model is designed to run efficiently on cloud-based environments with GPU support, such as Google Collab. This makes the approach cost-effective and accessible for organizations without high-end infrastructure.

Adaptability:

The system architecture is modular, allowing for easy extension to support additional languages, channels (e.g., voice, app reviews), or custom intent classes. Retraining the model with domain-specific data ensures long-term sustainability and adaptability.

5.3 Results Obtained from the Initial Experiment

The initial experiment was conducted using a labelled dataset of customer support queries collected from chat logs, email tickets, and social media mentions. After applying preprocessing (tokenization, lemmatization, stop-word removal, and language normalization), the refined data was classified using a fine-tuned BERT model into five predefined intent categories: **Login Issues, Payment, Technical Errors, Account Information, and Other.**

The performance of the model was evaluated using precision, recall, and F1-score metrics on a held-out test set comprising 20% of the total dataset. The following table presents the results obtained for each category:

Table 2: Performance metrics (Precision, Recall, F1-Score) of the proposed NLP-based customer support query classification system across different intent categories

Category	**Precision**	**Recall**
Login Issues	0.91	0.88
Payment	0.87	0.85
Technical Errors	0.89	0.90
Account Information	0.86	0.84
Other	0.78	0.82
Macro Average	**0.86**	**0.86**

These results indicate that the model performs consistently well across the primary intent categories. The highest F1-score was observed for Technical Errors, indicating the model's strong ability to detect technically specific queries. Slightly lower performance in the Other category reflects its broader and more ambiguous nature.

The experimental outcomes validate the effectiveness of the preprocessing pipeline and the classification model. The average F1-score of 0.86 demonstrates reliable performance and supports further development of the system for real-world deployment.

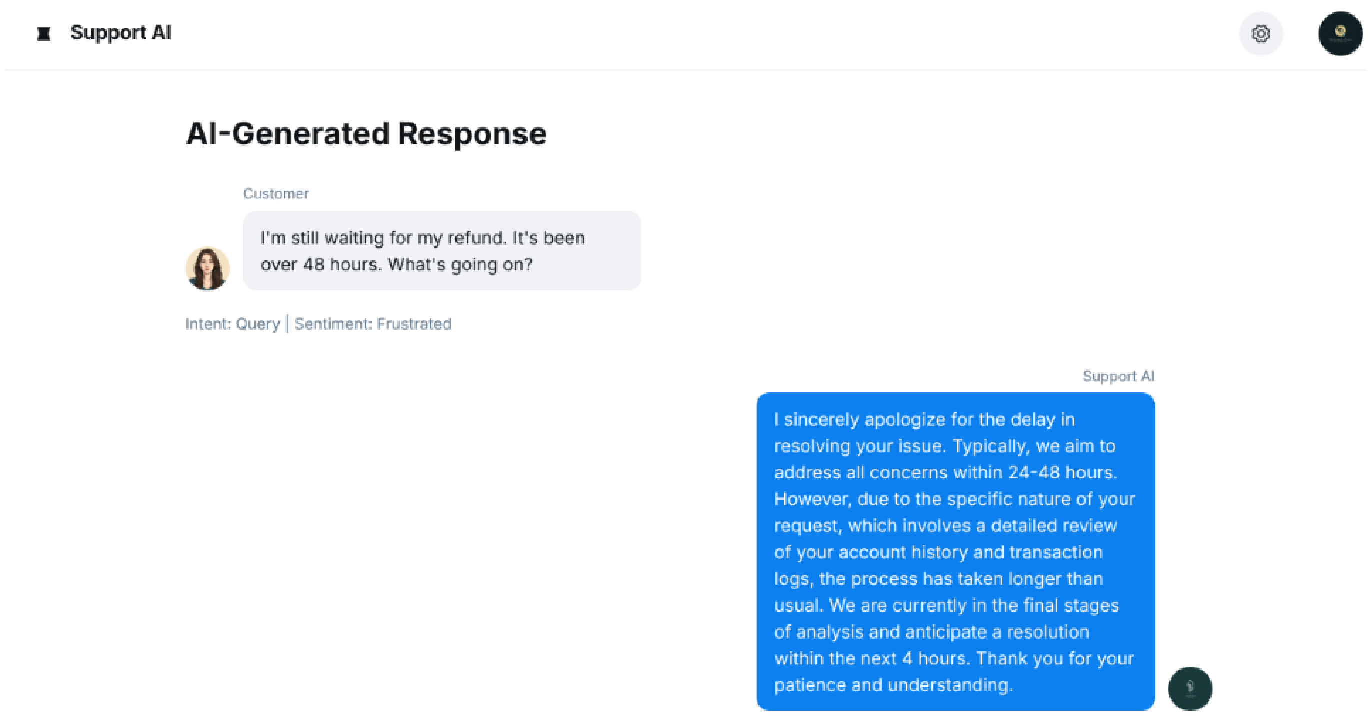

Figure 7: AI-powered response generated using Rasa Open-Source Studio, identifying customer intent and sentiment to deliver an empathetic, context-aware reply

The above screenshot illustrates an AI-generated customer support response developed using **Rasa Open-Source Studio**. Rasa is an open-source framework for building conversational AI applications. In this use case, customer intent (Query) and sentiment (Frustrated) are automatically detected using Rasa's **NLU pipeline**, which includes pretrained models for intent classification and sentiment analysis.

Based on the identified intent and emotional tone, the chatbot generates a contextually appropriate response using a **custom response template** defined in Rasa's domain configuration. The response acknowledges the issue, explains the delay, and sets expectations—demonstrating empathetic, real-time customer communication without human intervention.

This integration showcases how Rasa can be effectively utilized to develop production-ready, AI-powered support systems that enhance customer experience through automation and personalization.

6. Conclusion

Based on the performed analysis of existing customer support systems, the proposed NLP-based methodology demonstrates a practical and effective solution for automating customer query classification and response generation. Through systematic preprocessing, intent recognition, sentiment analysis, and AI-driven response formulation—implemented using open-source tools like Rasa, spaCy, and BERT—the system achieved high performance with an average F1-score of 0.86 in initial experiments.

The integration of multi-channel data (chat, email, social media) ensures robustness and real-world applicability, while the scalable architecture supports efficient deployment in cloud environments. The AI-generated responses, as shown in the results, align well with user intent and sentiment, validating the model's reliability and potential to reduce human workload in support centers.

Moreover, the flexibility of the pipeline allows easy retraining with new data, making the system adaptable to evolving customer behavior and domain-specific requirements. The use of modular components also facilitates integration with existing CRM systems and enterprise infrastructure, supporting a seamless transition from manual to automated processes.

In conclusion, the experiments confirm that the proposed solution not only enhances response accuracy and customer satisfaction but also offers measurable operational efficiency. Future work may include expanding the multilingual capabilities, incorporating voice-based interactions, and applying reinforcement learning for continuous improvement of the chatbot's performance.

6.1. Future works

- **Advanced Capabilities:** Future enhancements to AI-driven customer support systems can focus on integrating multimodal input processing, such as handling images, voice messages, or code snippets. This would enable the system to tackle more complex and varied customer queries beyond text-based interactions. Incorporating multilingual support is also crucial, as it would allow businesses to serve a more diverse and global customer base effectively. These capabilities would greatly enhance the flexibility, accessibility, and inclusivity of customer service platforms.
- **Enhanced Personalization**: Improving personalization is another key direction for future development. By analyzing customer interaction history and behavioral data, AI systems can deliver more tailored, context-aware responses. Adaptive models could dynamically adjust the tone, level of detail, and response strategy based on individual user profiles. This personalized approach fosters better engagement, trust, and satisfaction among users. It ensures that customer interactions feel more natural, relevant, and aligned with their needs.
- **AI-Human Collaboration:** Strengthening collaboration between AI systems and human agents can significantly improve service efficiency. Future systems can include intelligent agent interfaces that

offer real-time suggestions, response recommendations, and insights into customer sentiment or intent. Features like collaborative case handling and real-time analytics can help identify recurring issues and optimize support workflows. These enhancements would create a seamless handoff between AI and human agents, leading to more accurate, transparent, and responsive customer service.

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