Sentiment Analysis-Based Chatbot System to Enhance Customer Satisfaction in Technical Support Complaints Service for Telecommunications Companies

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Abstract: In the competitive world of telecommunications, a good customer technical support complaint service can make a difference. However, this business process still presents deficiencies in its quality. In the capital of Peru, there were 102,665 internet complaints and 38,621 cable television complaints. 9.27% and 9.97% of these, respectively, weren't resolved. In this sense, this research proposes the implementation of a chatbot, which incorporates GPT 3.5 as a sentiment analysis component, to reduce user dissatisfaction in this service process. To validate the proposal, experiments were conducted with 50 internet and cable television service owners to evaluate satisfaction and accuracy in recognizing their emotions. The results indicated that 86% of the respondents were satisfied with the chatbot service, and the satisfaction index reached 77.9, surpassing the minimum threshold of 75 points for providing quality customer service established by the industry. The methodology behind these results is detailed in the following research.

1 INTRODUCTION

In Peru, customer service quality indices are deficient. According to the report on service quality prepared by its Organismo Supervisor de Inversión Privada en Telecomunicaciones (OSIPTEL, 2021), none of the telecommunications companies operating there manage to meet the minimum threshold of 75 points necessary to guarantee quality service. This deficiency in service quality is clearly reflected in the complaints recorded during the year 2021 in the capital of the country, which were related to technical support, specifically in internet services (102,665) and cable television (38,621). Of these complaints, a significant percentage, 9,522 (9.27%) and 3,850 (9.97%) respectively, weren't satisfactorily resolved (OSIPTEL, 2022). In response to this situation and according to a survey conducted by Spiceworks (2018), chatbots emerged as a support tool to improve the customer service of companies, thus being the Customer Service/Customer Support department (20%) is positioned in third place among the departments that use chatbots the most in their daily tasks. This is observed in the research conducted by Kainathan et al. (2021), who present the chatbot XiaoIce, which employs anthropomorphic characteristics aimed at enhancing customer service. Similarly, Ngai et al. (2021) develop a knowledge-based chatbot to support customer service in e-commerce sales and marketing. However, despite the utility offered by customer service chatbots, current approaches are limited to specific task resolution or responding to inquiries using a predefined knowledge base. Additionally, the emotional dimension of the user during the interaction between human and chatbot is not adequately considered, an essential aspect for understanding and effectively addressing technical support-related complaints. Therefore, this research is based on applying the knowledge from these studies and extending it to the field of telecommunications, considering user sentiment

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analysis to achieve positive outcomes regarding customer satisfaction.

The key components of the research involve GPT-3.5, which will be used for recognizing user emotions. Furthermore, this technology is integrated within the VoiceFlow platform for the development of the chatbot, which in turn is integrated with Airtable to manage customer data.

That said, the main contributions are as follows:

- Implementation of a chatbot system using GPT-3.5 capable of recognizing user intention and emotion during interaction thanks to its sentiment analysis component.
- Application of anthropomorphic features such as empathy, warmth in conversations, and humor to enhance complaint handling.
- Validation of the proposed solution through experiments in a controlled environment involving 50 individuals who are subscribers of internet and/or cable television services.

On the other hand, the results of the present research, obtained after conducting experiments in a controlled environment with 50 users who are subscribers of internet and cable television services in the northern part of Lima, reveal that 86% of the participants expressed high satisfaction with the attention provided by the chatbot. Furthermore, 56% of the users highlighted the chatbot's ability to detect emotions as very high. In terms of the Customer Satisfaction Index calculated using the ACSI formula, a score of 77.9 was recorded, surpassing the minimum required score for satisfaction according to industry standards. These findings conclusively support the effectiveness and acceptance of the chatbot in improving the customer experience in the realm of internet and cable services.

This paper is distributed across 5 sections. Section 2 reviews related works on customer service chatbots. Then, it addresses the concepts and theories related to the background of this research, as well as the main contribution we will present in Section 3. Section 4 explains the experiments conducted in a controlled environment. Finally, this work concludes with the presentation of the conclusions derived from this project.

2 RELATED WORKS

Improving the customer service process has been a highly prominent research topic in recent years. This aspect has aroused deep interest among authors, who have addressed this challenge in various contexts, such as the health field, electronic commerce, and the insurance sector, among others. Therefore, in this section we present an overview of the different types of customer service chatbots, as well as the techniques used in their implementation and the characteristics that influence the improvement of the quality of assistance provided to users. The purpose of this section is to provide a solid understanding of the current situation and contribute to the advancement of research in this field.

Firstly, the results obtained by customer service chatbots are presented. In the study by El-Ansari and Beni-Hssane (2023), a personalized customer service chatbot was implemented in e-commerce applications with sentiment analysis features. The authors developed this chatbot aiming to enhance the user's intention recognition capability, considering their emotions to enhance their experience. In its development, they employed sentiment analysis techniques (VADER and BERT) and entity recognition (NER). In their experiment, 60 participants interacted with two versions of the chatbot, and the results showed that participants who interacted with the personalized version (9.13) reported higher levels of satisfaction compared to those who interacted with the non-personalized version (8.41). These findings demonstrate the effectiveness of the sentiment analysis personalization process in improving user satisfaction. Considering this finding, the present research will employ the GPT-3.5 model for intention and emotion recognition, aiming to achieve analogous results in terms of satisfaction, applying this methodology in the telecommunications domain.

Similarly, in the research conducted by Kasinathan et al (2021), a customizable multilingual chatbot for web applications is developed with the purpose of enabling SMEs to deploy their customer support chatbot service. Its functionalities include live chat, ticketing system, and tracking system. In a survey conducted with 27 participants out of a total of 50 invitations sent to IT departments of companies in Selangor, Malaysia, 77.8% of the surveyed companies expressed satisfaction with the use of the customer service chatbot. Based on these functionalities, the integration of a ticketing system with the chatbot of this solution has been considered, as the knowledge base used to generate responses has limitations, implying that sometimes a precise response that solves the user's problem is not provided. Endowing the chatbot with the functionality to generate tickets for technical visits that culminate in problem resolution in case the chatbot responses are insufficient contributes to making this type of system more efficient. In this regard, a ticketing system will be used in this research through integration with the Airtable system, but not for generating a ticket with an advisor, but rather for scheduling a technical visit to the telecommunications user.

On the other hand, techniques used in chatbot implementation have been found. In the study by Santos et al (2022), the Evatalk chatbot is developed using its own Chatbot Management Process (CMP), which is responsible for managing the chatbot's contents. Evatalk consists of three components, namely: EvaTalk Admin, Data Repository, and Model Trainer. In the latter, natural language processing (NPL) was employed to identify the user's intention. The chatbot was validated in customer technical support at the Virtual School of Government of Brazil. Its latest user satisfaction test reached 32.47% at the satisfied level and 50.29% at the very satisfied level. That being said, this proposal will employ NPL to identify the user's intention during the conversation since GPT-3.5 will be used, which is not only capable of recognizing the intention but also of discerning emotion in the context of telecommunications customer technical support.

Additionally, through a random online experiment in the study by Adam et al. (2021), empirical research was conducted to examine the effect of verbal cues incorporating an anthropomorphic design and the technique known as 'foot in the door' on the degree of compliance with requests made by the chatbot to users. In this study, social response theory and the concept of commitment-consistency were used as theoretical foundations to guide the research. For the development of the chatbot, they used IBM Watson Assistant's cloud service for natural language processing and dialogue management. The results of the experiment demonstrated that an anthropomorphic design, characterized by warm and empathetic responses, increases the likelihood of customers complying with the chatbot's requests, as 95% of the total participants complied with the chatbot's request compared to when these techniques were not used, which only represented 63%. Consequently, in this study, we will apply these characteristics but adapted to the context of complaint handling in a telecommunications company, focusing particularly on customer satisfaction survey compliance.

Similarly, in the study by Rahman and Watanobe (2023), examines the possibilities and challenges offered by ChatGPT in the educational context, both for students and educators in programming teaching. It is highlighted that ChatGPT presents multiple exciting advantages in education, including personalized feedback, increased accessibility, and interactive conversations. To investigate this, a survey was conducted with students and teachers from different academic levels, focusing on the impact of ChatGPT on programming learning and teaching. The survey addressed aspects such as participant identification, their experience in programming, the support provided by ChatGPT, its usefulness in problem-solving, as well as the degree of satisfaction with the system. The results revealed that most students (86.7%) found the suggestions provided by ChatGPT helpful in problem-solving. In this regard, these characteristics of ChatGPT, including the ability to address issues and facilitate interactive conversations, will be incorporated into the research, adapted to the realm of handling complaints in a telecommunications company.

Finally, concerning best practices in chatbot development, certain characteristics have been identified whose incorporation can contribute to improving the quality of assistance provided to users. Furthermore, in the research by Shin et al. (2023), the idea is proposed that the inclusion of humor by chatbots can play a fundamental role in their humanization and, consequently, in improving the customer experience. To support their hypotheses, they conducted an experiment involving 117 business university students. These students interacted with a chatbot in the context of a complaint about an incorrect bill issued by a fictitious telecommunications company. Participants engaged in two different interaction scenarios with the chatbot: one where the chatbot used humor and another where it did not. The results of the experiment indicated that when humor was incorporated, satisfaction with the service experienced a significant increase compared to the scenario without humor (M without humor = 4.06 vs. M with humor = 5.05). With this in mind, the inclusion of humor will be considered as a relevant feature in the implementation of the solution, albeit with a specific focus on managing complaints related to internet and cable services.

Finally, in the comparative satisfaction study conducted in Mainland China and Hong Kong by Liu et al. (2023), the importance of customer service chatbots being competent in timely issue resolution, showing empathy towards user concerns, and ensuring data privacy measures to increase usage intention is emphasized. This study employed a mixed-method approach integrating the Delone and McLean's Information System Success Model with privacy concerns. The results revealed that in

Mainland China, the model explained 70.4% of the variation in satisfaction and 51.4% of the variation in usage intention. In Hong Kong, the model explained 66.9% of the variation in satisfaction and 56% of the variation in usage intention. These results highlight the importance of competence, empathy, and security in user satisfaction and willingness to use customer service chatbots in these two regions. With that said, like previous studies, empathy and a competent approach will be considered as essential features for the proposed solution, but with a focus on complaint handling.

3 CONTEXT

3.1 Preliminary Concepts

The purpose of this section is to explain the necessary elements for the construction of a customer service chatbot, such as chatbot technology, natural language processing, ChatGPT, and sentiment analysis. In this section, the key concepts used in this work are presented.

3.1.1 Chatbot

It's a conversational agent based on artificial intelligence and machine learning technology that offers a variety of services through communication channels, such as text messages. It is designed to interact with human users in an automated manner (Jaspin et al., 2023).

3.1.2 Natural Language Processing

It is a technology that focuses on the interaction between the computer and human language. Additionally, it is used to analyse large amounts of information from various sources, such as patent databases, social networks, or crowdsourcing platforms, with the purpose of facilitating the search for promising solutions (Just, 2023).

3.1.3 ChatGPT

It is a pre-trained language model based on artificial intelligence that utilizes the GPT-3.5 architecture, developed by the company OpenAI. This model boasts remarkable capabilities in the field of natural language processing, enabling it to understand and respond to human language in real-time (Kocon et al., 2023

3.1.4 Sentiment Analysis

Sentiment analysis (SA) is a function of natural language processing aimed at extracting sentiments and evaluations expressed in texts. Its essence lies in the ability to discern how sentiment is manifested in a text (Bernabé et al., 2020).

3.2 Method

In this section, a detailed analysis of the design of the chatbot based on Natural Language Processing technology GPT 3.5 is presented, which enables the application of sentiment analysis, humor, warmth in conversations, and empathy. The Figure 1 illustrates the 4-layer architecture of ChatTelecom. Throughout the description of each layer, the five fundamental components that constitute the chatbot system will be addressed, each of which assumes a singular and essential function in the operation of the solution.

3.2.1 User Layer

This layer serves as the medium through which users interact with the chatbot. On one hand, telecommunication clients can use the WhatsApp application via a cell phone or laptop. On the other hand, technical support personnel handle complaints through a PC.

3.2.2 Presentation Layer

The main component within this layer is Whatsapp/front end. This component is a messaging platform developed by WhatsApp that allows companies to interact with their customers through this tool. WhatsApp was chosen as the front end because it is one of the main customer service channels in Peru across various industries. The presentation layer serves as an essential link between ChatTelecom, and conversations held via WhatsApp. On one hand, telecommunication service clients submit their complaints through WhatsApp messages. Lastly, when a complaint requires intervention from an advisor, i.e., a member of the technical support team, they handle and manage the complaint using the specialized version of WhatsApp Business. It's important to clarify that the role of technical support staff is to act as an intermediary in the communication, intervening only when the chatbot is unable to resolve the telecommunications customer's issue.

3.2.3 Service Layer

In the chatbot service process, it requests personal information from the internet and/or cable television service holder. Then, data validation proceeds with diagnosing the reported issue, classifying the breakdown. Once the type of breakdown the customer is facing is identified, multimedia content (images and PDFs) is requested to choose the most appropriate resolution step. Furthermore, to assist the customer in resolving their issue based on the chatbot's instructions, multimedia content will be sent. Hence, a file server is available to store these documents. In order to ensure better customer service, the GPT 3.5_Sentiment Analysis component allows adapting the conversation with the customer based on the detected emotion and applying anthropomorphic characteristics (empathy, warmth in conversations, and humor). Below is the application of its subcomponents.

Component Sentiment Analysis

The sentiment analysis component provided by the GPT 3.5 model was utilized. Initially, the choice of GPT 3.5 technology was made because it allows recognizing the user's intention during the conversation with an accuracy of 85.5%, possesses a massive corpus of data, and has the capability to adapt to different scenarios (Panda & Kaur, 2023; Zhu et al., 2023). However, since the problem addressed involves user emotional states being relevant to the service, it was necessary to fully leverage this model to enhance the user experience. The sentiment analysis component of this model was used as it allows adapting the chatbot's responses based on the recognized emotions, which can be expressed through texts or emojis. The application of sentiment analysis in the solution was carried out through the customization of prompts, where it was specified to recognize the user's emotion in order to adapt its response based on the detected emotion.

Application of Humor, Empathy, and Warmth in Conversations

The implementation of the chatbot considered these 3 anthropomorphic characteristics. Empathy was prioritized to offer users a closer and more personalized service experience. Additionally, warmth in responses was incorporated, recognizing that friendly responses foster more effective communication by making customers feel comfortable expressing their concerns. Furthermore, the use of humor was explored, acknowledging that well-employed humor can transform customer service interaction into a more enjoyable and memorable experience. These characteristics were defined as sections within the prompts of GPT 3.5. For their implementation, specific prompts within GPT 3.5 were used to guide the model to reflect empathy, maintain warmth in conversations, and employ relevant humor according to the detected emotion of the user. These components were refined during the chatbot training, which included keywords, key phrases, machine learning functionality provided by the platform, and constant interaction with users.

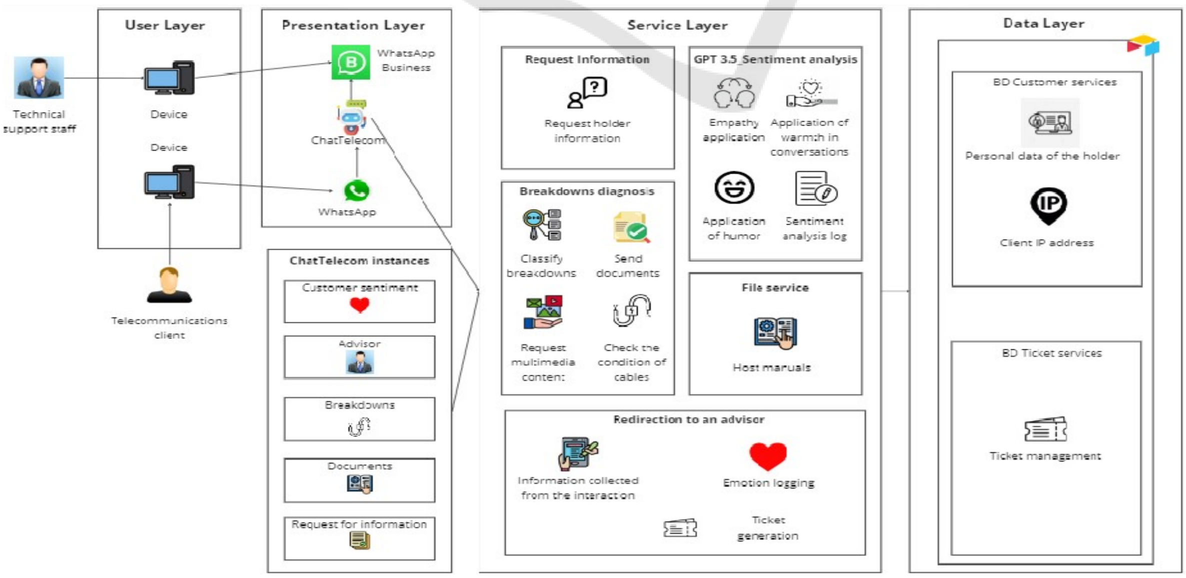

Figure 1: Architecture of the proposed ChatTelecom.

Finally, if the chatbot is unable to resolve the issue due to its complexity, the case is redirected to an advisor. This process involves the technical support staff continuing the resolution of the reported problem. During this process, the chatbot provides tools that facilitate the advisor's work, such as a summary of the interaction between the user and the chatbot, as well as the representation of the user's detected emotions through emojis.

3.2.4 Data Layer

In the data layer, data extraction is performed from the system Airtable. This data includes elements such as names, surnames, the National Identity Document (DNI) number, and the IP address corresponding to the internet and/or cable service holder. This extraction process is carried out with the primary purpose of validating the user's identity at the beginning of the assistance process. On the other hand, the client's IP address is used to simplify and expedite the assistance procedure by the advisor.

Thanks to the combination of these components within the ChatTelecom solution based on GPT 3.5, this research aims to achieve a 3% increase in customer satisfaction during the process of addressing complaints related to internet and cable television services within the telecommunications companies.

4 EXPERIMENTS

In this section, we will discuss the experiments carried out in the project, addressing both their design and execution, and present the conclusions derived from the results obtained throughout this process.

4.1 Experimental Protocol

The chatbot was developed using Voiceflow as this platform facilitated integration with GPT-3.5 and WhatsApp. On the other hand, for the experiments with ChatTelecom, specific equipment was required such as a PC with at least 8 GB of RAM and a 2.5 GHz processor, or a mobile device with at least 4 GB of RAM for a smooth experience.

The 50 participants, aged between 20 and 60 years old, reside in the northern region of the capital of Peru and are subscribers to internet and/or cable television services provided by a telecommunications company. User satisfaction was evaluated using a Likert scale from 1 to 5, and the chatbot's ability to recognize emotions was considered across 3 different scenarios. 35 participants were randomly selected for scenarios 1 and 3, with 20 assigned to scenario 1 and 15 to scenario 2. On the other hand, the remaining 15 were assigned to scenario 2, as they only had internet service. Below is the formula for the American Customer Satisfaction Index (ACSI), which was used to evaluate the user satisfaction index:

$$\mathrm{ACSI} = \left(\frac{\mathrm{N}}{\mathrm{n}}\right) * \left(\sum_{\mathrm{i}=1}^{\mathrm{n}} \mathrm{S_i} - \mathrm{D}\right) + \mathrm{D} \tag{1}$$

Where:

- N is the total number of responses in the survey.
- n is the number of responses considered in the calculation.
- S_i represents the ratings of each user.
- D is the benchmark satisfaction rating for the industry.

The experiment begins with the user presenting a complaint about internet and/or cable television service to the customer technical support chatbot. It starts by welcoming the user and proceeds to request necessary data for resolving the complaint. In the first scenario, the user informs the chatbot that their issue is the lack of clarity in the cable television channels. Simultaneously, the chatbot identifies that the user entered with a feeling of anger. Subsequently, after a series of specific questions related to the complaint process, the chatbot successfully resolves the incident, concluding with the delivery of a satisfaction survey regarding the assistance provided. In the second scenario, the user informs the chatbot that their problem is the loss of internet service. Simultaneously, the chatbot identifies that the user entered with a feeling of impatience as they requested a prompt solution. During the diagnosis of the fault, the chatbot asks the customer questions to identify the cause of the problem. Finally, the chatbot concludes that there is a router equipment misconfiguration issue, so it informs the customer that it is not able to resolve this type of faults but could refer them to an advisor who could address their case. Lastly, in the third scenario, the user details to the chatbot that their problem is the loss of cable television service. Simultaneously, the chatbot identifies that the user entered feeling concerned about their problem. After a series of questions aimed at resolving the problem, the chatbot determines that it is necessary to schedule a technical visit. Therefore, the problem is referred to a specialized advisor. The advisor concludes the assistance and proceeds to issue a ticket for the technical visit. Upon concluding the conversation flow with the chatbot, it generates a customer satisfaction survey that includes the following questions:

- How satisfied are you with the assistance you received today? 1: Very dissatisfied, 2: Dissatisfied, 3: Neutral, 4: Satisfied, 5: Very satisfied.
- How would you rate our ability to understand how you feel during the conversation? 1: Very low ability, 2: Low ability, 3: Average ability, 4: High ability, 5: Very high ability.

It's important to highlight that, according to the analysis of the studies conducted during the research, no studies have been found that offer a comparison with the emotional recognition capability indicators and the American Customer Satisfaction Index (ACSI) used in this research. Therefore, it is proposed to consider these indicators as new.

4.2 Results

In this section, the results of the satisfaction metrics and emotional recognition capacity of the user obtained from the experiments are presented.

On one hand, the experiment results revealed that the average rating given to the first satisfaction question is 4.4 on a scale ranging from 1 to 5. Additionally, the ACSI yielded a score of 77.9, surpassing the threshold of 75 points established as the quality standard in customer service in Peru (OSIPTEL, 2021).

$$ACSI = \left(\frac{50}{50}\right) * \left(\frac{222 - 75}{50}\right) + 75 \quad (2)$$

ACSI = 77.9

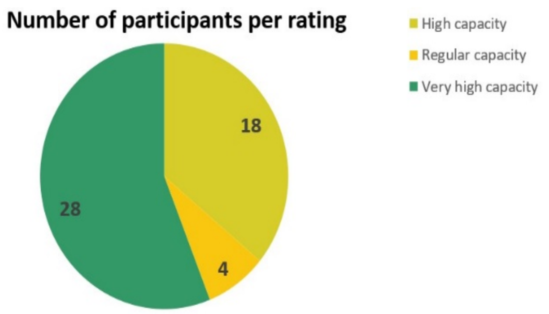

Figure 2: User Satisfaction Rate.

On the other hand, the user satisfaction rate achieved was 86% compared to other customer service chatbots mentioned in the related works section, as shown in Figure 2.

The results from these three scenarios were grouped to measure user satisfaction because, although the resolution methods differ, the goal in all cases is the same: to resolve the customer's problem and assess their satisfaction with the entire support process. Therefore, by grouping the scenarios, an integral view of the system's overall effectiveness is obtained, allowing for the identification of areas for improvement for both the chatbot and human intervention. Additionally, this grouping reflects a more realistic user experience, where satisfaction depends not only on who resolves the problem, but on how the overall support service is perceived.

On the other hand, based on the second question to evaluate the chatbot's ability to recognize how the user feels during the conversation, positive results were obtained.

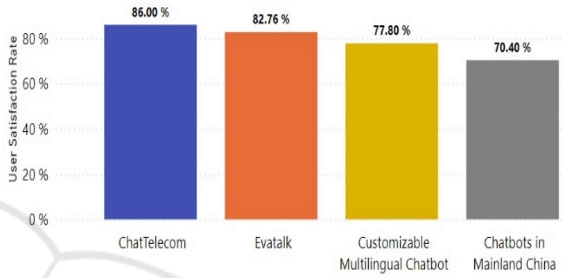

Figure 3: User emotional recognition rate.

According to Figure 3, most participants stated that their emotional state is taken into consideration during interactions with the chatbot. 56% of respondents rated this capability as very high, while 36% rated it as high. On the other hand, 8% rated it as having an average capacity to understand their emotional state. It's important to highlight that the user perceives that the chatbot recognizes their emotions due to its ability to respond appropriately and sensitively to their emotional expressions during the interaction. This is reflected in the chatbot's responses, the use of language, and the relevance of the solutions offered in relation to the emotions expressed by the user. These results are largely attributed to the sentiment analysis component of the system, which recognizes emotion and reflects it through emojis to mitigate it. Additionally, the application of empathy, warmth in conversations, and humor is considered to have a significant influence.

5 CONCLUSION

The application of humor, warmth in conversations, empathy, and sentiment analysis within the chatbot solution represents an advancement in the field of customer service. On one hand, it is evident that the sentiment analysis component of the GPT-3.5 model has been crucial in emotional recognition, as 56% of respondents rated the chatbot with a very high capacity to understand their emotional state. On the other hand, the combination of anthropomorphic features and sentiment analysis proved favourable for improving satisfaction, achieving a satisfaction rate of 86%. In conclusion, these components emerge as crucial factors for enhancing quality in the complaint handling process in the technical support domain for telecommunications companies. This understanding is supported by the fact that the satisfaction index obtained is 77.9, thus surpassing the minimum threshold of 75 established by the telecommunications industry in Peru as a parameter to ensure quality in the customer service process.

While the results obtained were indeed positive, we believe that there is room for additional improvements. We suggest integrating the chatbot with the customer network management systems of the telecommunications company, as well as utilizing an additional specific sentiment analysis component alongside the response model. Additionally, it is recommended to periodically update the chatbot's knowledge base, as the GPT-3.5 component handles data that may be outdated. This update should include the incorporation of new cases reported by customers, recent feedback, and current problems to provide more accurate answers to current problems. Furthermore, we estimate that a broader survey sample would have contributed to a more representative evaluation of the chatbot's effectiveness.

With the continuous progress of technology, it's expected that chatbots will acquire greater intelligence and capability to address a wider range of tasks. This advancement, consequently, would positively impact customer satisfaction and overall improvement of a company's service process. Therefore, we consider it imperative to continue conducting research employing current NLP models. Additionally, we express interest in future research evaluating similar components to those used in this work but applied in other customer service contexts, where user emotions also influence the service.

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