Journal of Infrastructure, Policy and Development 2024, 8(16), 10226.
https://doi.org/10.24294/jipd10226

Article

Exploring the impact of a Generative AI Voicebot on customer service quality in a telecommunications company in Peru

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CITATION

Gamboa-Cruzado J, Palomino-Morales B, Romero-Vega J, et al. (2024). Exploring the impact of a Generative AI Voicebot on customer service quality in a telecommunications company in Peru. Journal of Infrastructure, Policy and Development. 8(16): 10226. https://doi.org/10.24294/jipd10226

ARTICLE INFO

Received: 11 November 2024
Accepted: 3 December 2024
Available online: 24 December 2024

Abstract: Nowadays, customer service in telecommunications companies is often characterized by long waiting times and impersonal responses, leading to customer dissatisfaction, increased complaints, and higher operational costs. This study aims to optimize the customer service process through the implementation of a Generative AI Voicebot, developed using the SCRUMBAN methodology, which comprises seven phases: Objectives, To-Do Tasks, Analysis, Development, Testing, Deployment, and Completion. An experimental design was used with an experimental group and a control group, selecting a representative sample of 30 customer service processes for each evaluated indicator. The results showed a 34.72% reduction in the average time to resolve issues, a 33.12% decrease in service cancellation rates, and a 97% increase in customer satisfaction. The implications of this research suggest that the use of Generative AI In Voicebots can transform support strategies in service companies. In conclusion, the implementation of the Generative AI Voicebot has proven effective in significantly reducing resolution time and markedly increasing customer satisfaction. Future research is recommended to further explore the SCRUMBAN methodology and extend the use of Generative AI Voicebots in various business contexts.

Keywords: voicebot; generative AI; customer service; SCRUMBAN; telecommunications; quality

1. Introduction

Currently, telecommunications companies face criticism for their deficient customer service, characterized by long waiting times, impersonal responses, and complications in managing service cancellations. This issue generates dissatisfaction among users, increases operational costs, and has led to significant penalties due to ineffective practices and a high number of annual complaints.

Pawlik et al. (2022) proposed an improved method for intent recognition in virtual assistants, integrating emotional analysis to increase precision and effectiveness in customer service. On the other hand, Chandra (2020) developed a banking bot that used artificial intelligence to respond to queries about loans, accounts, and policies, enhancing customer service with accurate chat or voice responses. Similarly, Srisushma and Vijaya (2023) presented a banking voicebot with a hybrid Long Short-Term Memory (LSTM) model, which improved accuracy by 100% over existing algorithms, highlighting the importance of customer service for business success. Additionally, Noga (2023) identified opportunities and threats in the use of chatbots and voicebots in Polish public institutions, highlighting benefits, limitations, and risks through expert interviews and proposing solutions for digitalization. Plaza et al. (2022) proposed a method for emotion recognition in contact centers, enhancing the effectiveness of virtual assistants and human agents through conversation analysis to increase customer satisfaction.

Plaza and Pawlik (2021) analyzed how the development of Contact Center systems optimized the Key Performance Indicators (KPIs) such as Service Level, Cost per Contact, and Customer Satisfaction, using Artificial Intelligence (AI) for classification and emotional recognition. Moreover, Arora et al. (2023) emphasized MiWo Voicebot, an AI tool for migrant workers in India, aimed at informing them about constitutional rights, labor laws, and NGO resources to improve their quality of life. Antineskul et al. (2023) examined the impact of failures in telecommunications services on customer loyalty in Russia and proposed measures to mitigate their negative effects. Similarly, Voelskow et al. (2023) implemented a voicebot during the COVID-19 pandemic in Germany, significantly improving customer service in 20 local authorities by answering frequently asked questions. Gauthier et al. (2022) also introduced the first automatic voice assistant in Wolof, which provided details about Orange Senegal's Sargal program through oral interaction and responses based on audio recordings.

Tran et al. (2020) presented a voicebot integrating Text-to-Speech (TTS) and Speech-to-Text (STT) modules from FPT.AI, aimed at enhancing typical chatbots with text and voice responses, showing high accuracy in Vietnamese and lower accuracy in English. Similarly, Rohit et al. (2024) explored how voicebots transform interactions in e-commerce, emphasizing their influence on consumer engagement and the importance of cultural and linguistic adaptation. Likewise, Iparraguirre-Villanueva et al. (2023) implemented an intelligent agent that improved IT Incident Management, resulting in fewer unresolved cases and reduced resolution time, in addition to increased user satisfaction. Gamboa-Cruzado et al. (2022) reviewed the implementation of customer service bots, highlighting technological advancements and their expansion into sectors such as healthcare, transportation, and education. Finally, Casazola Cruz et al. (2021) examined the usability of customer service bots, underscoring the benefits and challenges of meeting user expectations.

The reviewed research has made significant contributions and revealed gaps and areas for improvement in the use of voicebots for customer service. The studies emphasize the versatility of these technologies, underscoring the need to adapt them to specific contexts and requirements (Plaza et al., 2022). For instance, Tran et al. (2020) underscore the linguistic limitations of voicebots, highlighting the need to explore more advanced solutions, such as the use of generative AI, which is addressed in this study. However, none of the studies examine the application of the SCRUMBAN methodology for the development of virtual assistants, despite its potential to increase flexibility and efficiency in project management. While Pawlik et al. (2022) and Plaza et al. (2022) emphasize the importance of emotional analysis in customer service, these works do not explore its integration with agile methodologies like SCRUMBAN, which is examined in this article. Our study addresses this gap by combining SCRUMBAN with a Generative AI-based Voicebot, offering an innovative approach to optimizing customer service. Additionally, there is a lack of rigorous hypothesis testing on the effectiveness of voicebots in customer service. Moreover, the use of generative AI, with its ability to provide more natural and precise responses, remains a highly promising area for further exploration in this field (Chandra, 2020). This article aims to optimize customer service through the implementation of a Generative AI-based Voicebot. Unlike previous studies, we explore the combination of Generative AI with agile methodologies to deliver more adaptable and effective solutions.

The paper is structured as follows: Section 2 discusses the theoretical background of the studied variables, followed by Section 3, which describes the methods and materials used. Section 4 explains the development of the Generative AI Voicebot using the SCRUMBAN methodology. Section 5 presents the results and discussion of the study, and finally, Section 6 offers the conclusions and suggestions for future research.

2. Theoretical background

The integration of AI into customer service systems has significantly transformed how telecommunications companies interact with their customers. Technologies such as Generative AI Voicebots are driving remarkable improvements in the efficiency and quality of customer service. However, significant challenges remain, such as the effective integration of these technologies with agile methodologies and the rigorous evaluation of their impact across different sectors—issues addressed in this study.

2.1. Generative AI Voicebot

A voicebot is a virtual program that uses AI and natural language processing (NLP) to conduct conversations by simulating human speech patterns, enabling seamless and natural interaction with users (Chandra, 2020). According to Diware et al. (2021), voicebots, like voice assistants, leverage AI, machine learning (ML), and speech recognition to interpret commands, mimic human conversations, and activate through keywords, thereby eliminating the need for a graphical interface.

The implementation of generative AI in voicebots has enabled these systems to generate more personalized and contextual responses, improving the user experience. Authors Plaza and Pawlik (2021) analyzed the impact of contact center systems on key performance indicators, finding that the implementation of advanced technologies such as voicebots significantly improves operational efficiency and customer satisfaction. However, these studies do not explore how to integrate these tools with agile methodologies to maximize adaptability, a gap this study addresses.

Adamopoulou and Moussiades (2020) point out that advancements in language models, such as GPT and LSTM, have led to the development of more sophisticated voicebots that better understand user needs. Despite these advancements, limitations in handling complex linguistic contexts have been identified, as noted by Tran et al. (2020), emphasizing the need to explore more advanced technologies such as generative AI, which this study applies.

In the telecommunications sector, speed and accuracy in service are crucial. Griol et al. (2019) highlight that integrating generative AI into customer service systems has significantly reduced incident resolution times and improved operational efficiency. However, existing studies do not systematically address how these improvements impact long-term customer experience, a topic this study examines through an empirical methodology.

2.2. Customer service

Loaiza et al. (2020) indicate that customer service is a process that facilitates the optimization of response times, improves service quality, demonstrates an increase in sales and profitability, and helps achieve business objectives. Similarly, Valenzuela Salazar et al. (2019) mention that customer service aims to attract consumers to the offered products or services, and it is the customers who assess the quality of the service received.

The adoption of AI technologies in customer service has shown substantial improvements in satisfaction and operational efficiency. Noga (2023) explored the use of chatbots and voicebots in public institutions, highlighting their ability to improve service accessibility and efficiency. Paschen et al. (2019) emphasize that these tools can reduce abandonment rates and increase customer retention. However, these studies do not evaluate how to integrate these technologies with more agile development methodologies to optimize their implementation, a gap this study seeks to address.

Hoyer et al. (2020) highlight that personalization and speed in responses from AI-based systems create a more satisfying user experience. Huang and Rust (2021) argue that generative AI provides solutions that are more accurate and tailored to individual customer needs. Despite these findings, there is no empirical evaluation of how these technologies impact specific sectors such as telecommunications, a gap addressed in this study.

2.3. SCRUMBAN

The successful implementation of Generative AI Voicebots requires development methodologies that enable flexibility and adaptability in complex projects. SCRUMBAN is a hybrid agile methodology that combines the principles of Scrum, such as short and structured iterations, with the visual and continuous elements of Kanban, such as workflow management and task prioritization. This approach provides a flexible and adaptable structure, improving project management by allowing a rapid response to emerging changes and needs during development (see **Figure 1**).

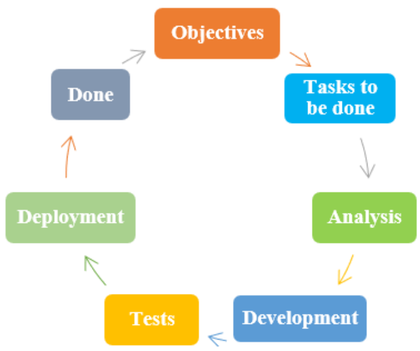

Figure 1. Phases of the SCRUMBAN methodology.

The methodology illustrates an iterative cycle, fostering constant team collaboration and workflow optimization. This approach is particularly useful in the development of Generative AI Voicebots, where technical requirements and user needs evolve continuously. Despite its potential, few studies have applied SCRUMBAN in the development of voicebots, leaving a gap that this work addresses.

Iparraguirre-Villanueva et al. (2023) developed an intelligent agent for incident management using agile methodologies, which improved development efficiency and adaptation to changing user needs. Similarly, Gamboa-Cruzado et al. (2022) emphasize the importance of agile approaches to ensure user-centered implementations. However, no prior research combines SCRUMBAN with the use of generative AI in voicebots, representing a unique contribution of this work

3. Methods and materials

This section provides a detailed explanation of the methodology used to conduct the study's analysis, describing the operationalization of variables, research design, sample characterization, data collection procedure, and hypothesis formulation. The primary objective is to present the subject with precision and ensure the reliability of the achieved results, offering a clear and comprehensive understanding of the employed approach.

a) Research purpose

The objective of this study is to evaluate the effectiveness of a Generative AI-driven Voicebot in improving customer service quality, utilizing the SCRUMBAN approach. To this end, a hybrid model is proposed, integrating agile tools with predictive analytics.

b) Scope of the research

The application context focuses on telecommunications companies, where customer service is critical. These organizations face challenges such as managing high interaction volumes and improving user experience.

The analysis was conducted on projects implemented by NOC CENTURYLINK E.I.R.L., which uses advanced digital tools and demonstrates a notable level of technological adoption. However, the study focused on medium- and large-scale projects within the company's infrastructure, limiting the applicability of the results to smaller or less complex projects.

c) Operationalization of variables

Table 1. Operationalization of the dependent variable.

Indicator	Index	Unit of Measurement	Observation Unit
Average waiting time	[4–12]	Minutes/client	Manual Review
Average incident resolution time	[5–20]	Minutes/incident	Manual Review
Service cancellation rate	[15–40]	(%)	Manual Review
Call abandonment rate	[12–45]	(%)	Manual Review
Customer satisfaction level	Strongly disagree, Disagree, Neither agree nor disagree, Agree, Strongly agree	Likert scale	Direct Observation

Table 1 shows the indicators, their corresponding indices, and the related units of measurement and observation for the dependent variable considered in this research.

d) Research design

An applied and pure experimental research approach was used, implementing a Post-Test Control Group design.

RGe X O1

RGc — O2

In this design, an experimental group (RGe) was randomly selected, followed by the implementation of the Generative AI Voicebot (X) in the company. Five specific indicators (O1) were measured 30 times to evaluate performance. Additionally, 30 randomly selected processes (RGc) served as the control group (O2), without the application of the Voicebot (--). This data facilitated the comparison and assessment of differences in results between the experimental and control groups, considering the Voicebot intervention.

e) Universe and sample

The study's population includes all Customer Service processes in Spanish-speaking American companies providing fiber-optic Internet services, with N = Indeterminate. The sample was limited to Customer Service processes in the company NOC CENTURYLINK E.I.R.L., with a sample size of n = 30, which may restrict the generalizability of the results to other cultural or economic contexts. Additionally, the data collected comes exclusively from an organization with advanced technological infrastructure, introducing a bias toward regions with lower digital development.

f) Data collection procedure

Observation sheets were used as the primary data collection instrument, applied through direct and indirect observation techniques. Additionally, an extensive review of academic sources was conducted to enrich the analysis.

g) Hypothesis statement

The following hypotheses were proposed:

H1: Implementing a Generative AI Voicebot developed using the SCRUMBAN methodology reduces the average waiting time.

H2: Incorporating a Generative AI Voicebot designed under the SCRUMBAN methodology decreases the average time required to resolve issues.

H3: Adopting a Generative AI Voicebot developed with the SCRUMBAN methodology reduces the service cancellation rate.

H4: Using a Generative AI Voicebot developed with the SCRUMBAN methodology decreases the call abandonment rate.

H5: Implementing a Generative AI Voicebot created using the SCRUMBAN methodology increases customer satisfaction levels.

To test the hypotheses, specific solutions were proposed for each of the selected indicators to evaluate their effectiveness and obtain precise results within the study context:

$\mu 1$ = Population Mean (H1, H2, H3, H4) for the Post-Test of the Control Group (Gc).

$\mu 2$ = Population Mean (H1, H2, H3, H4) for the Post-Test of the Experimental Group (Ge).

where: $H_0: \mu_1 \leq \mu_2$ y $H_1: \mu_1 > \mu_2$.

Additionally:

$\mu 1$ = Population Mean (H5) for the Post-Test of the Gc.

$\mu 2$ = Population Mean (H5) for the Post-Test of the Ge.

where: $H_0: \mu_1 \geq \mu_2$ y $H_1: \mu_1 < \mu_2$.

Finally, a normality evaluation was conducted using the Anderson-Darling test (see refer to Section 5.2. Normality test), followed by a descriptive statistical analysis and hypothesis validation using Student's *t*-test and the Mann-Whitney *U* test, performed with Minitab 21 software.

4. Case study

This section outlines the development process of the Generative AI Voicebot using the SCRUMBAN methodology. This methodology is structured into seven phases: Objectives, To-Do Tasks, Analysis, Development, Testing, Deployment, and Done.

4.1. Objectives

In this phase, the fundamental hardware and software resources required for developing the Generative AI Voicebot are identified, ensuring that all technological components align with the project requirements. This selection establishes a robust and functional infrastructure that supports each development stage, from initial setup to effective deployment. Specific details of these resources are presented in **Table 2**.

Table 2. Hardware and software resources.

Technology	Resources
Equipment	1 Pc Intel Core I5 10400 CPU, 1 Laptop AMD Ryzen 5 4500U
IDE	Visual Studio
Programming language	Dart
Framework	Flutter
Development platform	Dialogflow

4.2. To-Do Tasks

In this phase, the necessary requirements for developing the Generative AI Voicebot were gathered through an interview, which was directly requested by the General Manager of NOC CENTURYLINK E.I.R.L. This requirements collection is essential to align the Voicebot's functionalities with the company's expectations and project goals. (See **Tables 3** and **4** for a detailed breakdown of the requirements and specifications).

Table 3. Functional requirements.

Code	Functional Requirement
RF1	The system must be able to understand and process natural language queries.
RF2	The system must be able to identify the user's intent behind the request.
RF3	The system must provide accurate and relevant responses to user queries.
RF4	The system must keep a record of user interactions.
RF5	The system must be able to adapt and improve its comprehensibility over time.
RF6	The system must be able to handle multiple users simultaneously.
RF7	The system must allow the customer to request assistance or technical support when needed.
RF8	The system must be able to process and respond to voice commands from the user.

Table 4. Non-functional requirements.

Code	Non-functional Requirement
RNF1	The system must be intuitive and easy to use, with a user-friendly interface.
RNF2	The system must be available 24 hours a day, 7 days a week to ensure continuous service.
RNF3	The system must be able to handle multiple requests efficiently and with fast response times
RNF4	The system must be scalable to accommodate an increase in user volume without compromising performance.
RNF5	The system must be easy to maintain and upgrade to ensure optimal performance over time.
RNF6	The system must be reliable and error-free to provide a consistent user experience.

4.3. Analysis

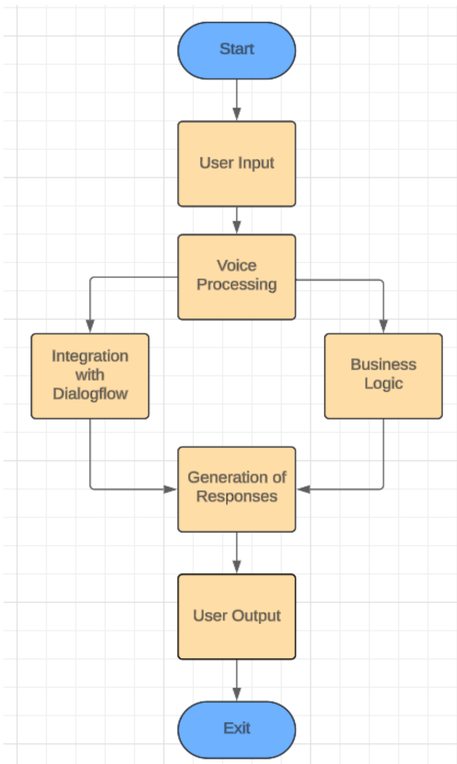

Figure 2. Flow diagram.

In this phase, once the task has been selected and assigned, a comprehensive analysis is conducted to determine its feasibility within the context of the project. This analysis helps identify potential obstacles and ensures that the available resources are sufficient to meet the established requirements. **Figure 2** shows the Voicebot's Flow Diagram, which outlines the detailed and sequential process the system will follow to achieve the goals set during the initial stage.

4.4. Development

This phase presents the application's architecture, an essential structure to understand the internal functioning and organization of the Generative AI Voicebot. **Figure 3** illustrates this architecture, emphasizing how the various components interact to facilitate efficient and accurate communication, enhancing customer service in the telecommunications sector.

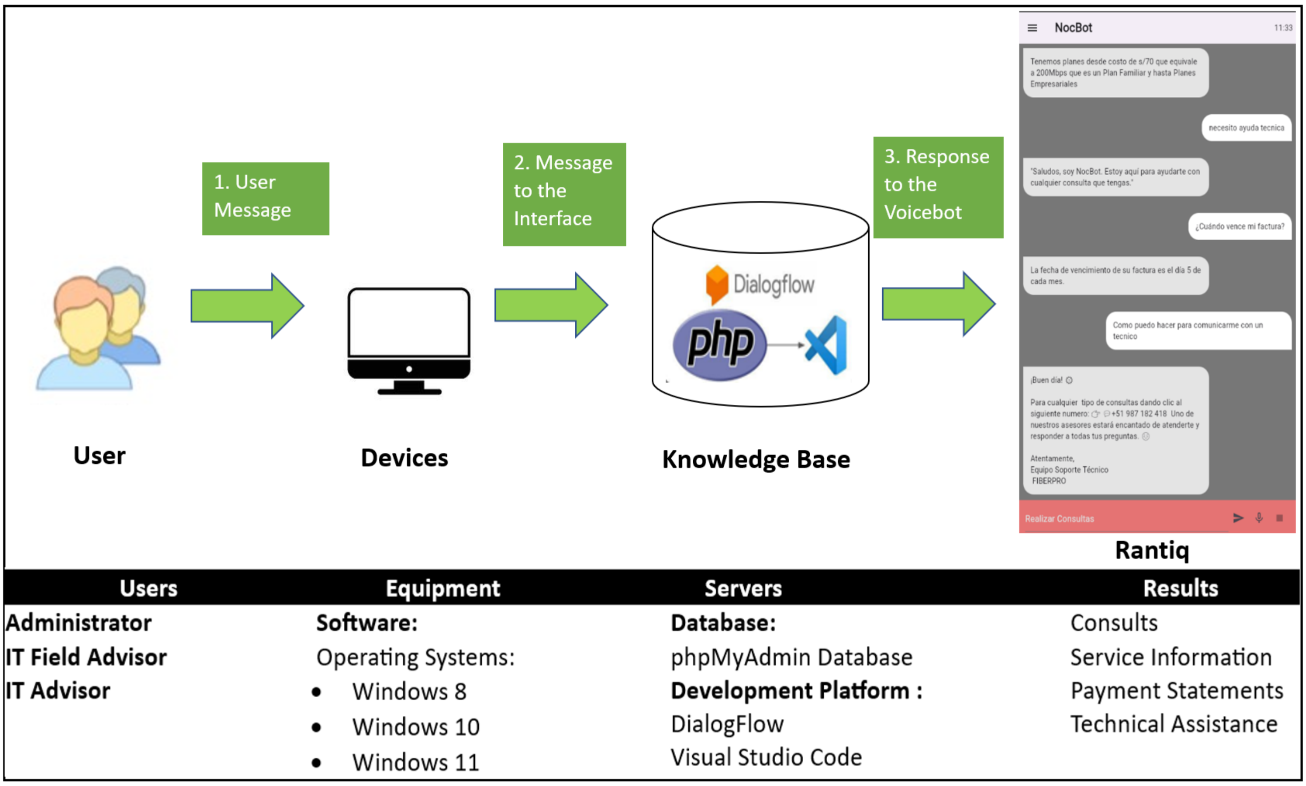

Figure 3. Application architecture.

In addition to defining the application architecture (**Figure 3**), this phase includes the design of the Generative AI Voicebot prototypes, covering key functionalities such as Login, Request Assistance, Make Inquiries, and Voice Interaction, shown in **Figures 4** and **5**. These prototypes represent the essential interface and interactions needed to deliver effective and seamless customer service in the telecommunications field.

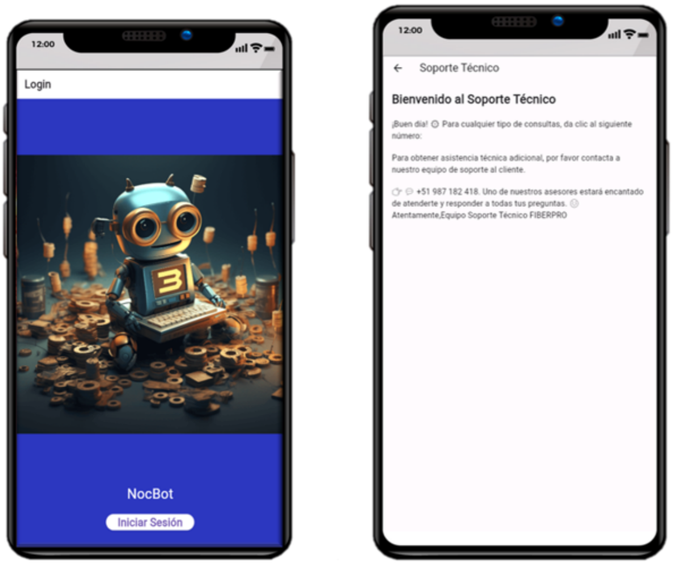

Figure 4. Login and request assistance prototype.

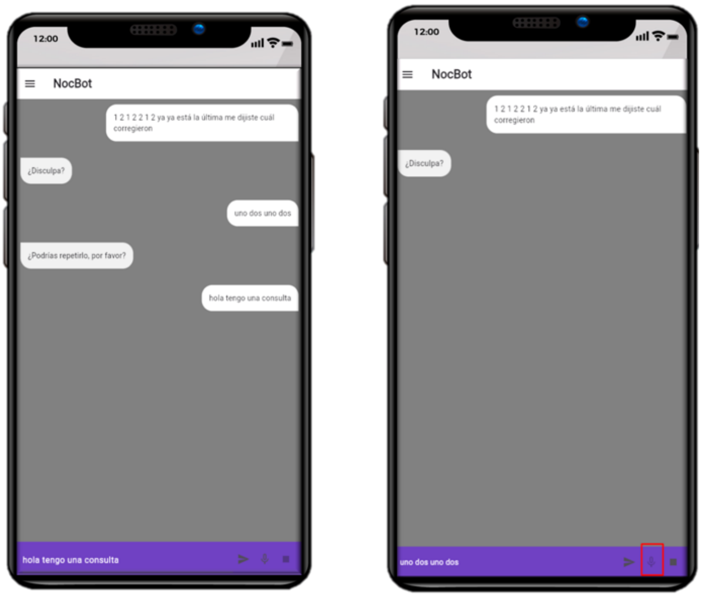

Figure 5. Inquiry and voice interaction prototype.

4.5. Testing

In this phase, acceptance tests for the Generative AI Voicebot are conducted, as shown in **Figures 6–8**. These tests are crucial for verifying performance and ensuring the system meets the client's requirements and expectations, guaranteeing optimal operation before the final deployment.

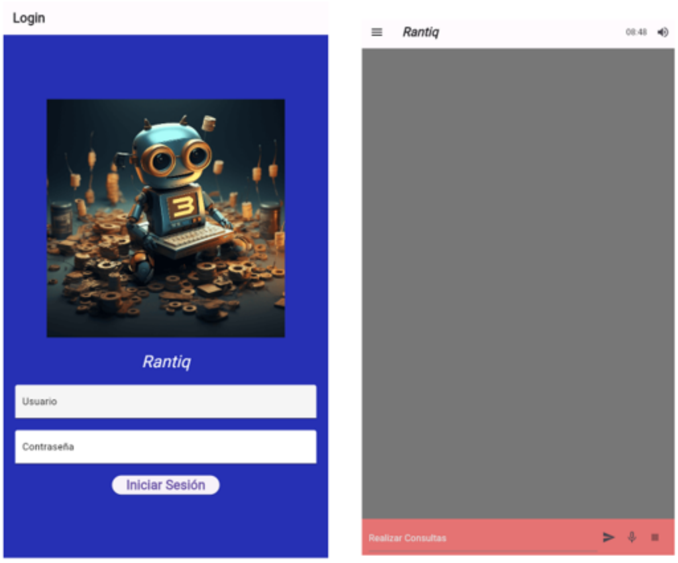

Figure 6. Login acceptance test.

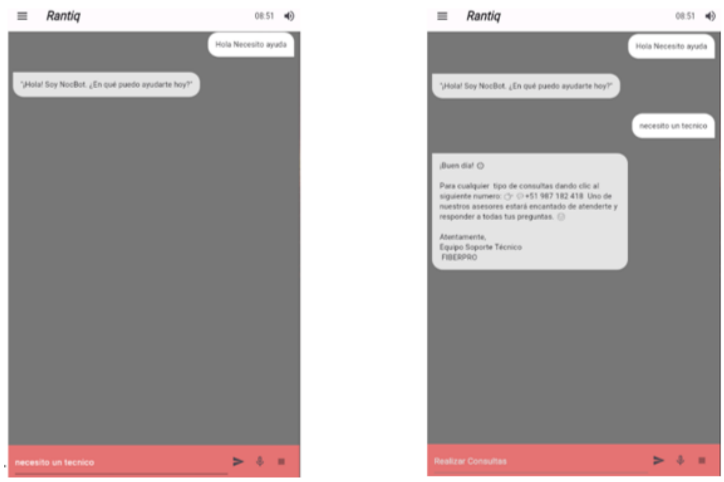

Figure 7. Acceptance test for inquiry function.

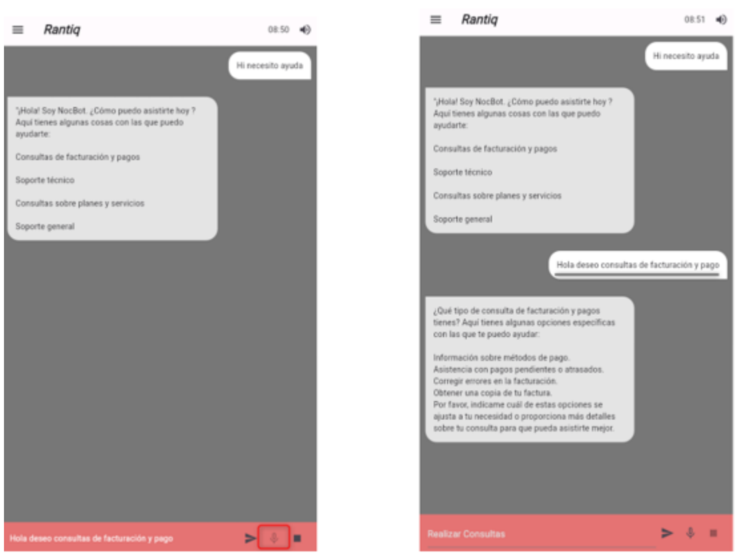

Figure 8. Voice interaction acceptance test.

4.6. Deployment

During this phase of the Voicebot development, multiple deployments are carried out following standardized processes. As shown in **Figure 9**, the Voicebot's intents are defined, initiating the training process of the system to ensure it responds effectively to the client's needs and expectations.

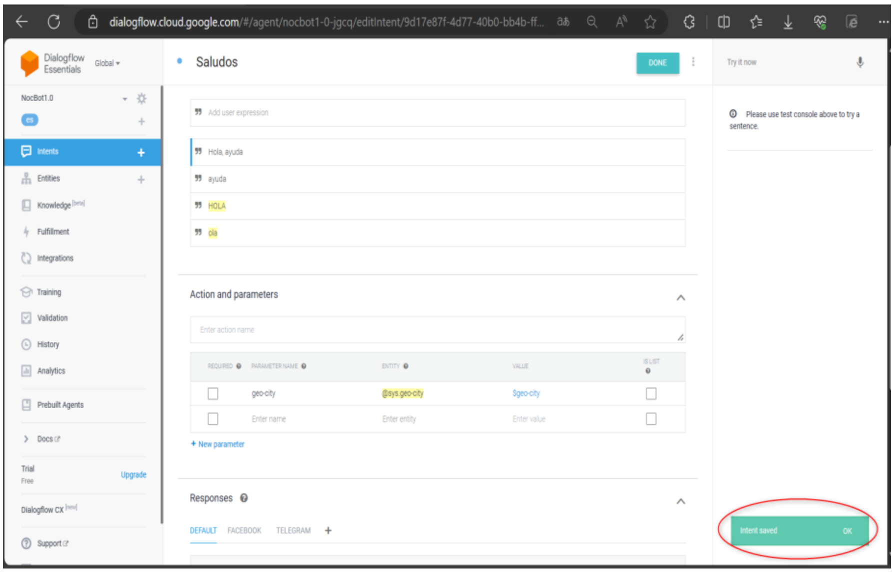

Figure 9. Voicebot training.

4.7. Completion

In this phase, after completing the optimal training of the Voicebot, the application is considered finalized upon achieving 100% of the established training requirements. This milestone marks the conclusion of the project, allowing for its practical implementation (see **Figure 10**).

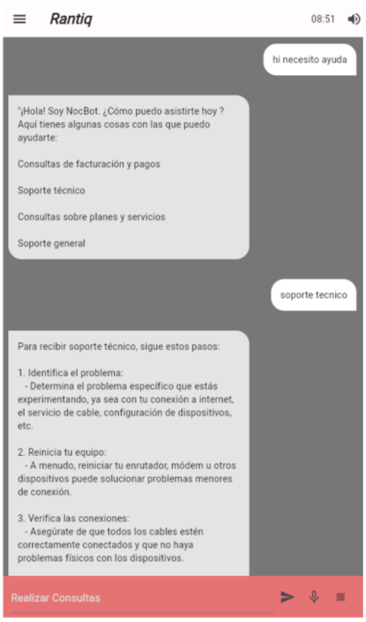

Figure 10. Rantiq.

5. Results and discussion

This section presents the obtained results and their corresponding discussion. Experimental data are showcased, normality tests are examined, and findings are analyzed in depth. Additionally, both descriptive and inferential statistical analyses, including hypothesis testing, are conducted to validate the study results.

5.1. Experimental results

Measurements were conducted on 30 processes for each indicator in the control group (Gc) and the experimental group (Ge), evaluating the following indicators: Average waiting time, Average incident resolution time, Service cancellation rate, Call abandonment rate, and Customer satisfaction level (see **Tables 5** and **6**).

Specific formulas were applied to calculate the corresponding values for each of the four quantitative indicators:

$$Tpe = \frac{(\sum \text{Waiting Times})}{(\sum \text{Total Number of ClientsWho Waited})} \tag{1}$$

$$Tpri = \frac{\text{Total Resolution Time of Cases}}{\text{Total Numberof Resolved Incidents}} \tag{2}$$

$$Tcs = \frac{\text{\#Deactivated Lines}}{Total\ Current\ Lines\ in\ the\ Database} \times 100 \tag{3}$$

$$Tal = \frac{\#Abandoned\ Calls}{\#Received\ Calls} \times 100 \tag{4}$$

where:

Tpe: Average waiting time, Tpri: Average incident resolution time, Tcs: Service cancellation rate, and Tal: Call abandonment rate.

Table 5. Post-test results for Gc and Ge for I_1, I_2, I_3.

	I_1: Average waiting time (min. per client)		I_2: Average incident resolution time (min. per incident)		I_3: Service cancellation rate (%)	
N°	**Gc Post-test**	**Ge Post-test**	**Gc Post-test**	**Ge Post-test**	**Gc Post-test**	**Ge Post-test**
1	7.52	4.38	6.90	5.27	30.74	15.75
2	9.03	5.71	8.41	8.10	34.56	16.82
3	8.25	4.54	9.48	8.40	29.75	17.29
4	8.99	5.99	8.60	4.99	34.56	18.47
5	9.45	7.69	10.19	7.23	39.50	19.63
6	8.81	7.10	10.59	7.10	33.33	20.11
7	9.36	7.70	12.79	7.70	25.80	21.28
8	8.51	6.99	19.14	9.48	28.52	22.94
9	10.05	6.54	18.94	12.05	29.75	23.57
10	11.47	8.18	17.86	7.53	30.63	24.66
11	7.78	6.67	13.84	6.67	34.69	25.14
12	8.50	7.53	8.64	7.53	35.52	26.37

Table 5. (*Continued*).

	I_1: Average waiting time (min. per client)		I_2: Average incident resolution time (min. per incident)		I_3: Service cancellation rate (%)	
N°	**Gc Post-test**	**Ge Post-test**	**Gc Post-test**	**Ge Post-test**	**Gc Post-test**	**Ge Post-test**
13	9.10	8.48	12.99	8.48	38.81	27.19
14	9.65	7.16	14.45	7.16	28.03	25.92
15	9.81	8.44	12.05	8.44	35.08	15.91
16	9.12	7.48	13.55	7.48	34.56	16.46
17	9.18	7.58	10.70	9.18	23.45	17.65
18	9.48	8.41	15.26	9.48	29.75	18.26
19	10.05	9.00	14.52	10.05	34.56	19.38
20	9.06	7.14	14.49	7.14	27.16	20.52
21	10.21	9.18	12.44	9.18	25.80	20.43
22	9.41	6.67	12.10	6.49	38.81	22.39
23	9.47	6.34	10.70	8.11	33.33	23.75
24	10.07	7.08	7.43	7.08	24.45	22.05
25	9.75	7.74	11.52	7.74	25.33	21.69
26	9.06	8.58	13.63	8.58	29.16	26.51
27	9.76	7.75	11.55	7.75	35.80	27.06
28	9.57	5.14	11.00	6.14	34.45	28.17
29	8.25	7.96	11.84	8.25	37.05	15.33
30	9.98	8.26	11.73	11.08	31.05	16.99

Table 6. Post-test results for Gc and Ge for I_4 and I_5.

	I_4: Call abandonment rate (%)		I_5: Customer satisfaction level (Likert scale)	
N°	**Gc Post-test**	**Ge Post-test**	**Gc Post-test**	**Ge Post-test**
1	24.74	18.88	Disagree	Agree
2	27.34	25.46	Strongly disagree	Agree
3	35.21	19.55	Disagree	Agree
4	31.78	16.78	Neither agree nor disagree	Strongly agree
5	28.42	14.28	Neither agree nor disagree	Agree
6	32.15	15.42	Disagree	Strongly agree
7	25.67	22.22	Disagree	Agree
8	26.93	17.85	Neither agree nor disagree	Strongly agree
9	29.75	22.41	Disagree	Agree
10	34.12	14.04	Strongly disagree	Agree
11	40.05	12.84	Neither agree nor disagree	Strongly agree
12	39.27	16.27	Disagree	Strongly agree
13	38.59	20.34	Disagree	Agree
14	27.88	23.91	Neither agree nor disagree	Agree
15	34.76	17.41	Agree	Strongly agree
16	37.19	18.59	Disagree	Agree
17	25.43	24.57	Disagree	Agree

Table 6. (*Continued*).

	I_4: Call abandonment rate (%)		I_5: Customer satisfaction level (Likert scale)	
***N*°**	**Gc Post-test**	**Ge Post-test**	**Gc Post-test**	**Ge Post-test**
18	30.65	13.45	Neither agree nor disagree	Agree
19	29.87	18.59	Disagree	Agree
20	26.56	17.14	Strongly disagree	Agree
21	36.09	18.46	Neither agree nor disagree	Strongly agree
22	28.74	12.12	Disagree	Agree
23	33.98	13.84	Disagree	Agree
24	41.23	12.34	Neither agree nor disagree	Agree
25	36.84	14.10	Strongly disagree	Agree
26	33.26	17.71	Disagree	Strongly agree
27	37.55	16.78	Disagree	Agree
28	44.48	25.91	Neither agree nor disagree	Agree
29	24.57	15.28	Disagree	Strongly agree
30	28.91	16.78	Strongly disagree	Strongly agree

5.2. Normality test

To assess whether the sample data follows a normal distribution, the Anderson-Darling normality test was applied. This test calculates a statistic that measures the differences between the observed and expected values under the null hypothesis of normality. The resulting *p*-value indicates whether the data exhibit normal behavior or not (see **Figures 11–14**).

I_1: Average waiting time.

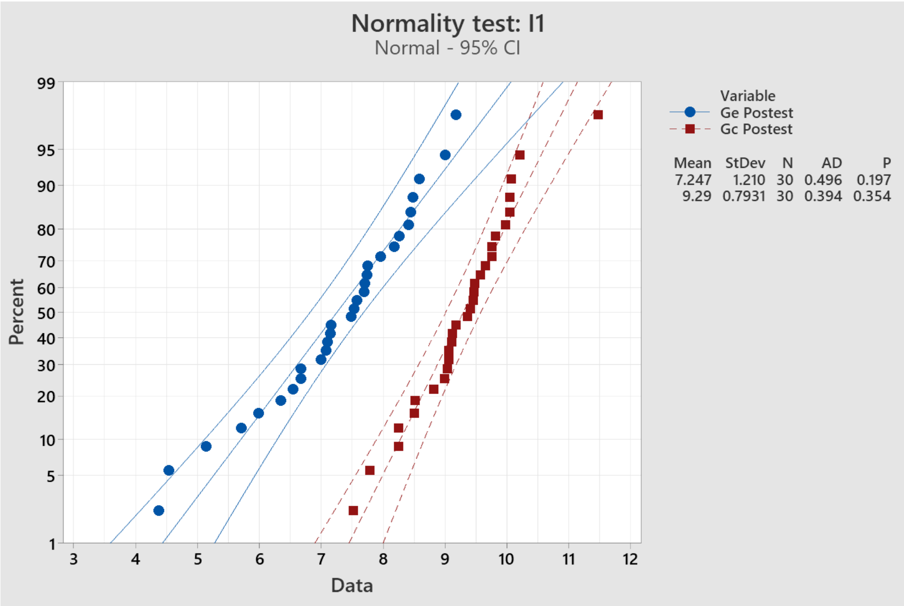

Figure 11. Normality test: I_1.

I_2: Average incident resolution time.

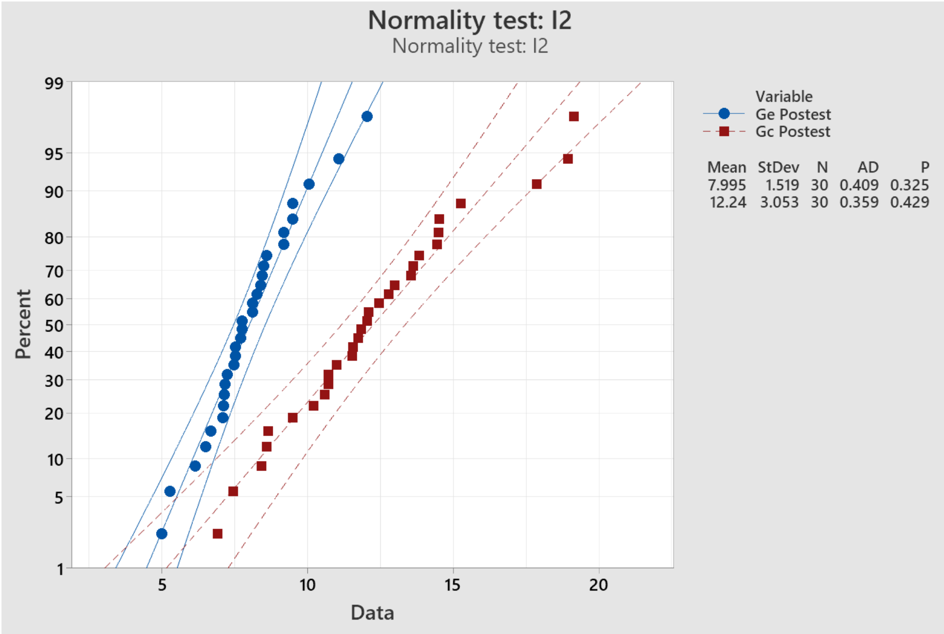

Figure 12. Normality test: I_2.

I_3: Service cancellation rate.

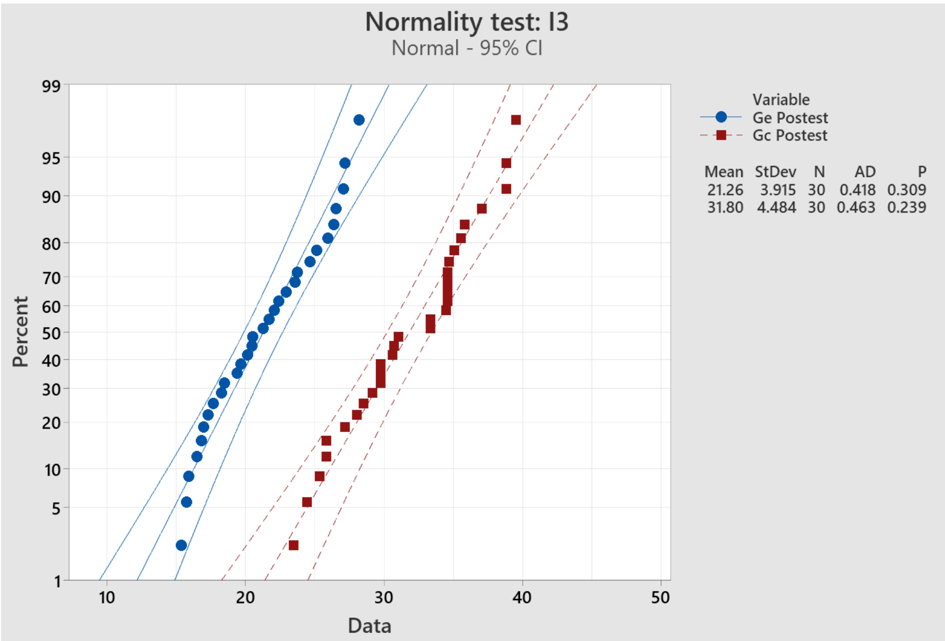

Figure 13. Normality test: I_3.

I_4: Call abandonment rate.

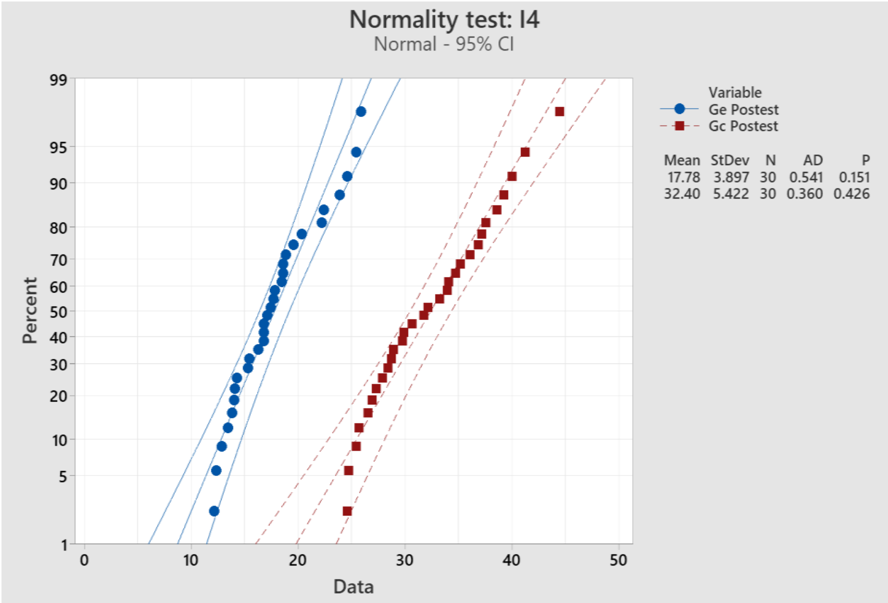

Figure 14. Normality test: I_4.

Since the p-value for all four indicators (I_1, I_2, I_3, I_4) exceeds the significance level set at $\alpha = 0.05$, it is concluded that the data obtained for each indicator (Ge and Gc) follows a normal distribution. Based on this finding, the parametric Student's t-test was selected to conduct the hypothesis testing, considering that the data meets the normality requirements.

5.3. Discussion of results

This section presents a detailed analysis that includes both descriptive and inferential statistics through hypothesis testing applied to the data collected in this research, aiming to validate the results and draw substantiated conclusions.

a) Using descriptive statistics

A comprehensive analysis of the main data properties is provided, using measures of central tendency and dispersion to characterize the behavior of the studied variables, thus enabling an accurate and informed understanding of the observed patterns in the dataset (see **Tables 7** and **8**).

Table 7. Descriptive statistics results.

Sample	n	Mean	StDev	AD	p-value
I_1: Post-test (Gc)	30	9.29	0.7931	0.394	0.354
I_1: Post-test (Ge)		7.247	1.210	0.496	0.197
I_2: Post-test (Gc)	30	12.24	3.053	0.359	0.429
I_2: Post-test (Ge)		7.995	1.519	0.409	0.325
I_3: Post-test (Gc)	30	31.80	4.484	0.463	0.239
I_3: Post-test (Ge)		21.26	3.915	0.418	0.309
I_4: Post-test (Gc)	30	32.40	5.422	0.360	0.426
I_4: Post-test (Ge)		17.78	3.897	0.541	0.151

Indicator I_1 (average waiting time): The results of the normality test ($p > 0.05$) suggest that the data for both the control group (Gc) and experimental group (Ge) follow a normal distribution, allowing for valid comparisons. The experimental group shows a lower mean (7.25) compared to the control group (9.29), indicating a potential reduction in average waiting time due to the implementation of the generative AI-powered Voicebot.

Indicator I_2 (average incident resolution time): The mean resolution time is significantly lower in the experimental group (7.99) compared to the control group (12.24), suggesting that the Voicebot can speed up the incident resolution process. The normality of the data is also confirmed, enabling accurate comparative analysis.

Indicator I_3 (service cancellation rate): The experimental group shows a lower cancellation rate (21.26) compared to the control group (31.80), which could reflect higher customer retention through improved service experience with the Voicebot. The normal distribution of the data supports the validity of this observation.

Indicator I_4 (call abandonment rate): The call abandonment rate in the experimental group (17.78) is lower than in the control group (32.40), indicating that the Voicebot has helped reduce the number of abandoned calls. The results of the normality test allow reliable comparisons between the two groups.

Indicator I_1 (average waiting time): With a confidence interval ranging from 6.80 to 7.70 minutes per client and a kurtosis of 0.324, the waiting time shows a slight distribution toward the center. The negative skewness (−0.772) suggests moderately concentrated waiting times toward the lower end, with the third quartile (Q3) at 8.20 minutes, representing the majority of waiting times within an efficient range. These findings are similar to those reported by Singh et al. (2023), who achieved a 28.95% reduction in the average waiting time for users. Likewise, the results align with Antineskul et al. (2023), who found a significant 63.63% decrease in average waiting time. Madhusudhan and Gupta (2024) also observed an equivalent reduction in waiting time, achieving a 96% decrease. Additionally, these results surpass those reported by Dávila et al. (2023), who recorded an average waiting time of 13.93 minutes with their proposed system. Finally, these outcomes are comparable to those of Lara Gavilánez et al. (2021), who reported a 39.63% reduction in average waiting time. An average waiting time of less than 8.20 minutes for most clients indicates a significant improvement in service perception. This is crucial for reducing customer dissatisfaction and enhancing the overall efficiency of the service process.

Table 8. Summary of results for the indicators.

Sample	*n*	95% confidence intervals for the mean	Kurtosis	Skewness	Q3
I_1: Post-test (Ge)	30	6.7951–7.6989 minutes/client	0.323980	−0.771960	8.20
I_2: Post-test (Ge)	30	7.4281–8.5625 minutes/incident	1.06332	0.54812	8.73
I_3: Post-test (Ge)	30	19.794–22.718%	−1.20389	0.16829	24.780
I_4: Post-test (Ge)	30	16.322–19.232%	−0.393910	0.601556	19.748

Indicator I_2 (average incident resolution time): The confidence interval of 7.43 to 8.56 minutes per incident indicates a relatively low average resolution time, with positive kurtosis (1.063) and positive skewness (0.548), showing a slight tendency toward higher resolution times. Q3, at 8.73 minutes, suggests that most resolutions occur below this threshold, maintaining system efficiency. The data reflect similarity with results from Ticona Gregorio (2022), who achieved a 36.71% reduction in the average resolution time for incidents. Comparatively, Plaza and Pawlik (2021) obtained similar results, reaching an average resolution time of 6 minutes. Conversely, these results surpass those of Iparraguirre-Villanueva et al. (2023), who achieved a 63% reduction, resulting in an average resolution time of 31.6 minutes per incident using an intelligent agent. Paolino et al. (2019) also reported a comparable 39.61% reduction in resolution time. Finally, these results outperform those from Tapia-Guarnizo and Campoverde-Molina (2019), who reported a 20.90% reduction in incident resolution time. Maintaining a resolution time below 8.73 minutes ensures timely responses to customer issues, boosting satisfaction and minimizing the escalation of unresolved issues.

Indicator I_3 (service cancellation rate): The confidence interval of 19.79% to 22.72% reflects a moderate cancellation rate, with negative kurtosis (−1.204) and slight positive skewness (0.168), indicating a balanced distribution centered on moderate values. Q3, at 24.78%, suggests that most cancellations are below this value. These findings are comparable to those of Saputro et al. (2021), who reported an average cancellation rate of 72.98%. Similarly, they surpass the results of Sudharsan and Ganesh (2019), who recorded an average cancellation rate of 11.37%. These results are also better than those of Ribeiro et al. (2024), who reported an average cancellation rate of 14%. The results align with those of Dikareva-Brugman et al. (2023), who noted a 47% service cancellation rate. Finally, they are comparable to Ouf et al. (2024), who found a significant 45.38% reduction in the service cancellation rate. A low cancellation rate suggests favorable customer retention. Keeping most values below 24.78% can enhance customer loyalty and reduce service user turnover.

Indicator I_4 (call abandonment rate): The confidence interval between 16.32% and 19.23% indicates a low call abandonment rate, with kurtosis close to 0 (−0.394), suggesting a normal distribution. The positive skewness (0.602) and Q3 of 19.748% indicate that most abandonments fall within these values, demonstrating stability in customer retention. These results are similar to those of Zallman et al. (2019), who observed a significant 76.92% reduction in call abandonment rates. Additionally, they outperform those of Plaza and Pawlik (2021), who found an average call abandonment rate of 8.0%. The results are also comparable to Waheed et al. (2024), who reported an average call abandonment rate of 33.63%. These outcomes surpass those of Dávila et al. (2023), who achieved a 9.56% reduction in average call abandonment rates. Finally, they are similar to those of Ansari et al. (2024), who reported a significant 61.66% reduction in call abandonment rates. A low call abandonment rate, with most values below 19.748%, indicates good handling of incoming calls and favorable user retention, strengthening the customer experience and reinforcing the positive perception of the service.

b) Using inferential statistics: hypothesis testing

Hypothesis tests were conducted to determine the statistical significance of the results, validating the findings and drawing relevant inferences about the analyzed population, thereby strengthening the robustness of the conclusions (see **Tables 9** and **10**).

Table 9. Hypothesis testing for parametric indicators.

Sample	n	H_0	t-value	p-value
I_1: Post-test (Gc) I_1: Post-test (Ge)	30	$\mu_1 \leq \mu_2$	7.73	0.000
I_2: Post-test (Gc) I_2: Post-test (Ge)	30	$\mu_1 \leq \mu_2$	6.83	0.000
I_3: Post-test (Gc) I_3: Post-test (Ge)	30	$\mu_1 \leq \mu_2$	9.70	0.000
I_4: Post-test (Gc) I_4: Post-test (Ge)	30	$\mu_1 \leq \mu_2$	12.00	0.000

The results show that for all indicators (I_1, I_2, I_3, I_4), the p-value of 0.000 is below the established significance level ($\alpha = 0.05$), providing sufficient evidence to reject the null hypothesis (H_0) and validate the alternative hypothesis (H_1). With a sample size of 30, the t-values obtained for each indicator are 7.73, 6.83, 9.70, and 12.00, respectively, confirming that the intervention implemented in the experimental group is statistically significant in terms of improvements in waiting and resolution times, as well as in the reduction of cancellation and call abandonment rates.

For Indicator I_1, Antineskul et al. (2023) showed optimal results, concluding that reducing average waiting time and effective incident management are key for customer loyalty in telecommunications. The significant reduction in the average waiting time in the experimental group indicates an improvement in service efficiency, directly contributing to increased customer satisfaction and a positive service perception.

For Indicator I_2, the results were similar to those of Ticona Gregorio (2022), who determined a value of ($p = 0.000$), accepting H1 and concluding that the application achieved a reduction in the average incident resolution time from the beginning of the study. The decrease in resolution time in the experimental group suggests that the implemented processes optimize incident management, which is crucial for improving customer trust and retention.

For Indicator I_3, the study by Ribeiro et al. (2024) showed optimal results by determining the p-value at 0.000, rejecting H0, and concluding that the service cancellation rate was reduced in telecommunications companies. The reduction in the cancellation rate in the experimental group shows that improvements in customer service positively influence customer loyalty, reducing churn and strengthening service stability.

For Indicator I_4, the results align with those obtained by Ansari et al. (2024), who significantly reduced the call abandonment rate, concluding that the study is optimal for minimizing the call abandonment rate in call centers. The reduction in the call abandonment rate in the experimental group implies better handling of incoming calls, which is essential for minimizing customer frustration and improving retention during customer service interactions.

Table 10. Hypothesis testing for non-parametric indicators.

Sample	*n*	H_0	*w*-value	*p*-value
I_5: Post-test (Gc) I_5: Post-test (Ge)	30	$\mu_1 \geq \mu_2$	475.00	0.000

The data for Indicator I_5 (Customer satisfaction level) show a *p*-value of 0.000, which is below the significance level ($\alpha = 0.05$). This provides sufficient evidence to reject the null hypothesis (H_0: $\mu_1 \geq \mu_2$) in favor of the alternative hypothesis, indicating that customer satisfaction in the experimental group is significantly higher than in the control group. The *w*-value of 475.00 reinforces the significance of this finding in a sample of 30 observations.

The results align with those obtained by Ruiz-Rodríguez et al. (2022), who determined a *w*-value of 0.000, providing sufficient evidence to accept the alternative hypothesis (H_1). Therefore, the test is statistically significant. Additionally, it was concluded that the system increases customer satisfaction levels. Similarly, these results align with those of Burgos-Medina et al. (2021), who also improved user satisfaction by implementing the system. This result suggests that the intervention's implementation in the experimental group has significantly improved customer satisfaction. This implies that advanced technology, such as the Generative AI Voicebot, can be an effective resource for optimizing the customer service experience, increasing satisfaction, and potentially fostering customer loyalty toward the company.

6. Conclusions and future research

The implementation of a Generative AI Voicebot in the context of customer service within telecommunications demonstrated a significant impact on process optimization and customer experience improvement. The results show a 34.72% reduction in the average incident resolution time and a 33.12% decrease in the service cancellation rate, reflecting a more agile and efficient service. Additionally, there was a notable reduction in call abandonment rates, accompanied by a 97% increase in customer satisfaction, as confirmed by responses on a Likert scale, where most users in the experimental group rated their experience as "agree" or "strongly agree". The comparison between the experimental group and the control group highlights the superiority of the Generative AI-based solution. For instance, the average resolution time in the experimental group was consistently over 30% shorter than in the control group, indicating that the Voicebot is effective in tasks requiring quick and personalized responses. The statistical values obtained, supported by normality and inferential tests, validate the reliability of the results and reinforce the positive impact of the SCRUMBAN methodology on the implementation of this technology. In terms of customer satisfaction, the Voicebot significantly exceeded traditional expectations in the sector. This suggests that the system's ability to understand and address queries naturally and personally contributes directly to a positive perception of the service. Therefore, this technology positions itself as a transformative tool for telecommunications companies, with the potential to be replicated in other sectors such as financial services and retail. In conclusion, the research not only validates the impact of Generative AI Voicebots on customer service but also highlights the importance of integrating robust methodological approaches such as SCRUMBAN to maximize operational benefits.

The study presents limitations that should be considered when interpreting its results. The sample size, limited to 30 processes per indicator, may not reflect variability in broader scenarios. Additionally, the results focus on the telecommunications sector, limiting their generalization to other sectors. Finally, external factors, such as the complexity of the queries or customers' familiarity with similar technologies, were not exhaustively controlled, which may have influenced the results. For future research, it is suggested to expand the sample size, allowing for validation of the consistency of the results across more diverse and extended contexts. It would also be valuable to explore the impact of Generative AI Voicebots in other sectors, such as finance or retail, to assess the generalizability of the findings. Lastly, it would be interesting to evaluate the system's implementation in multicultural and multilingual contexts, analyzing differences in user interaction and acceptance.

Author contributions: Conceptualization, BPM and JRV; methodology, JGC and FAG; software, SAE and ANM; formal analysis, BPM, JRV and JGC; investigation, SAE and JGC; writing—original draft preparation, BPM, ANM and NPR; writing—review and editing, NPR, JRV and SAE; supervision, JRV and JGC; project administration, BPM, NPR and SAE. All authors have read and agreed to the published version of the manuscript.

Conflict of interest: The authors declare no conflict of interest.

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