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# Customer satisfaction in logistics: an analysis of chatbots in the leading companies of Colombia, Peru, and Ecuador

## *Satisfacción del cliente en la logística: un análisis de chatbots en las empresas líderes de Colombia, Perú y Ecuador*

Pedro Ramos De Santis
Professor at Escuela Superior Politécnica del Litoral, Ecuador
pramos@espol.edu.ec
https://orcid.org/0000-0002-5968-481X

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**Abstract:** the article analyzes the potential effectiveness of chatbots on enhancing consumer service in the logistics industry, assessing the performance of ten prominent companies in Colombia, Peru, and Ecuador (CPE region). These companies, situated in the logistics services sector, play a crucial role in the supply chain, offering specialized services encompassing transportation, storage, and other areas within their economic activities. The study, involving 1250 individual B2C (business-to-consumer) users of chatbots, focused on analyzing the effectiveness of these tools and their impact on customer satisfaction. Through multiple regression analysis, key factors influencing customer satisfaction were identified, such as the ability to address issues, detailed knowledge of the company, autonomy in issue resolution, grammatical accuracy, and overall reputation. The results underscore the significant potential of chatbots to enhance customer service in logistics, emphasizing their effectiveness in issue resolution, familiarity with products and services, autonomy in issue resolution, grammatical correctness, and user recommendations. These findings are vital for the logistics sector, highlighting the transformative role of chatbots in elevating customer satisfaction and operational efficiency through technological integration.

**Keywords:** chatbot, effectiveness, logistics, multiple regression, service.

**Resumen:** este artículo analiza el impacto potencial de los chatbots en el mejoramiento del servicio al cliente en la industria logística, evaluando el rendimiento de diez destacadas empresas en Colombia, Perú y Ecuador (zona CPE). Estas empresas, insertas en el sector de servicios logísticos, desempeñan un papel crucial en la cadena de suministro, ofreciendo servicios especializados que abarcan transporte, almacenamiento y otras áreas dentro de su actividad económica. El estudio, que incluyó a 1250 usuarios individuales tipo B2C (empresa a consumidor) de chatbots, se enfocó en analizar la efectividad de estas herramientas y su repercusión en la conformidad del cliente. Mediante análisis de regresión múltiple, se identificaron elementos fundamentales que inciden en la satisfacción del cliente, como la capacidad de abordar problemas, el conocimiento detallado de la empresa, la autonomía en la resolución de problemas, la precisión gramatical y la reputación general. Los resultados destacan el potencial de los agentes virtuales para mejorar significativamente la atención al consumidor en la logística, señalando su eficacia en la resolución de problemas, familiaridad con productos y servicios, autonomía en la resolución de problemas, corrección gramatical y recomendaciones de usuarios. Estos hallazgos son cruciales para el sector logístico, subrayando el papel transformador de los chatbots en la elevación de la satisfacción del cliente y la eficiencia operativa mediante la integración tecnológica.

**Palabras clave:** chatbot, efectividad, logística, regresión múltiple, servicio.

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# Introduction

## Using chatbots in customer service

Global logistics, driven by the rise of e-commerce, demands efficiency in customer service, leading companies to use technologies such as chatbots (Caldarini *et al*., 2022). These artificial intelligence (AI) programs simulate human conversations, providing continuous assistance without human intervention and improving customer satisfaction with information about orders, shipments and schedules (Nicolescu and Turodache, 2022).

The growing use of chatbots spans companies of different sizes and sectors, offering personalized interactions by simulating human conversations. Chatbot research has evolved since 2000 (Caldarini *et al*., 2022). In logistics, chatbots manage customer inquiries and complaints in a cost-effective way, providing ongoing attention, improving response times and handling repetitive tasks (Davenport *et al*., 2020).

Integrated into various channels, such as websites and social networks, chatbots adapt to the client's preferred method and understand natural language for more human responses (Illescas-Manzano *et al*., 2021; Ridha and Haura, 2022). The quality of their responses depends on carefully designed data and training algorithms, although in complex situations some clients prefer human interaction (Sarker, 2021; Trappey *et al*., 2021; Adamapolou and Moussiades, 2020; Xu *et al*., 2020).

The versatility of chatbots stands out by adapting to different industries and business scales, offering personalized support to democratize efficient customer service solutions (Perifanis and Kitsios, 2023). Companies under study, specializing in B2C services, distinguish by fast deliveries and tools for traceability, prioritizing customer service with fast responses, effective solutions and efficient transaction management. The study collected data from 1,250 B2C users to understand the correspondence between interaction with chatbots and the overall consumer compliance level.

Despite its growing popularity, understanding the impact of chatbots on customer satisfaction in logistics is essential. Its effective implementation improves the customer experience by providing fast and accurate responses.

## Chatbots and Artificial Intelligence (AI)

Technology is advancing, and chatbots along with Artificial Intelligence (AI) are evolving, offering fascinating potential for human interaction with machines. These technologies influence daily life and the business environment. Chatbots, also called conversational agents, simulate human conversations through chat interfaces, providing automated responses limited to specific tasks using natural language interpretation algorithms (Adamapolou and Moussiades, 2020).

AI seeks to develop systems with human capabilities, such as learning and reasoning, and is used to make chatbots understand and respond to natural language more intelligently (Collins *et al*., 2021). It explores aspects such as auditory recognition, computer vision, and natural language processing.

The key difference is that chatbots are specific applications for interacting in a chat, while AI creates intelligent systems for various tasks. Chatbots, using AI techniques, have limited capacity to understand natural language and follow predefined patterns (Lin *et al*., 2023). Instead, AI, focusing on natural language processing (NLP), uses advanced algorithms to understand the meaning, intent, and context of human language, enabling more complex responses.

The integration of chatbots and AI systems promises more seamless and personalized interactions, as well as intelligent solutions across multiple industries. While chatbots improve customer service, AI expands possibilities in terms of automation and decision-making, significantly impacting how we interact with technology in the modern world.

In particular, the synergy between chatbots and AI systems not only improves natural language comprehension, but also allows these programs to evolve over time. AI's continuous lear-


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ning capability ensures that chatbots are adapted to changing customer needs and be updated without constant intervention (Aldoseri *et al*., 2023).

## Challenges and limitations of chatbots in customer service

Although virtual assistants offer numerous benefits to logistics companies, several challenges and limitations need to be considered, including technological limitations, customer preferences, and ethical concerns. Mageira *et al*. (2022) point out that chatbots face limitations in understanding and responding to natural language. Although they can recognize phrases and keywords, understanding the context can be challenging, causing customer misunderstandings and frustration, affecting company perception. According to Marjerison *et al*. (2022), another major challenge is the need for continuous maintenance and updates of chatbot programming. Adapting to changes in queries and customer preferences requires continuous investment of time and resources to maintain the effectiveness of the chatbot.

Customer preferences pose challenges, as some prefer the efficiency of chatbots, while others opt for human interaction, especially in sensitive situations (Hudiyono, 2022). Transparency is key to mitigating resistance, clearly indicating when they interact with a chatbot or human agent (Meyer *et al*., 2022).

Chatbots' limitations can affect their performance in logistics customer service, generating dissatisfaction and damaging the brand's reputation. Ethical concerns also arise, such as the need to program them to preserve client privacy and confidentiality (Khanum & Mustafa, 2022). In addition, the risk of chatbots perpetuating prejudice or discrimination should be considered, requiring careful design and monitoring to avoid problems (Brendel *et al*., 2022).

Adopting chatbots in customer service is not a universal solution (Caldarini *et al*., 2022; Zhang *et al*., 2021). They may not be suitable for all types of customer queries, and companies should evaluate the type of queries they receive to determine whether chatbots can effectively address them (Mohd *et al*., 2022). Complex inquiries or customer complaints may require human intervention to resolve satisfactorily.

While chatbots offer logistical benefits, such as improved service and reduced costs, they face challenges. Although efficient in common consultations, they can fail in emotional or specialized situations. Companies must identify areas of maximum value and ensure a smooth transition to human support when necessary (Kooli., 2023). Technological limitations, customer preferences, and ethical concerns are possible obstacles to adopting chatbots. Therefore, companies should carefully assess their suitability for their needs and ensure ethical and effective implementation.

Previous research has examined the effectiveness of chatbots in consumer care in various industries, including retail (Tran *et al*., 2021; Jiang *et al*., 2022; Tan and Liew 2022; Fan *et al*., 2023), healthcare (Abd-Alrazaq *et al*., 2020; Calvaresi *et al*., 2021, Rathnayaka *et al*., 2022; Puspitasari *et al*., 2022), tourism (Ivanov 2020; Zhang *et al*., 2022; Rafiq *et al*., 2022; Pereira *et al*., 2022) and finance (OECD, 2021; Nguyen *et al*., 2021; Lappeman *et al*., 2022; Ho and Chow, 2023; Sung *et al*., 2022). Chen and Florence (2021), measured the effectiveness of AI-enabled virtual assistants in consumer service using AnyLogic Simulation through scenario analysis, providing managerial implications for average system time, response rate, level of satisfaction, and cost savings. This helped companies understand the impact of adopting AI-enabled chatbots on customer service.

The logistics sector is highly competitive and, in this context, chatbots are gaining increasing acceptance and use in the industry, with many companies adopting them to improve their customer service offerings (Jenneboer *et al*., 2022). Although popular, the effectiveness of chatbots in this sector requires further study, evaluating their impact on satisfaction, response time and problem solving (Um *et al*., 2020). This study is relevant to ensure an efficient and reliable service in logistics, where customers demand accurate information about their orders to maintain loyalty. Although chatbots can be a solution, it is essential to evaluate their effectiveness in this context (Wetzel and Hofmann, 2020).

In short, the purpose of this research is to examine the effectiveness of chatbots in the logistics industry and their influence on customer satisfaction. This research is crucial to understanding how logistics companies can improve customer service and maintain a competitive advantage in the industry. In addition, it will provide valuable insights into the implementation of chatbots in logistics by identifying their strengths and limitations and assessing their impact on critical customer service metrics.

## Materials and method

This research was carried out to assess the performance of chatbots in the customer service of logistics companies in the CPE region. Methodological aspects are detailed below, including the selection of participants, the research instrument and the collection of demographic data.

### Participants and selection

The study involved 1,250 B2C clients from ten leading logistics companies specializing in services for end consumers operating in the CPE zone. The selection of these companies met specific criteria, such as the volume of operations, annual revenues, reputation and prestige in the sector, international presence, technological innovation, customer feedback and impact on the industry. These individuals were invited to participate through specific invitations sent by email to those customers who had used the chatbot services in the last six months. All participants expressed their willingness to be part of the study and provided informed consent before completing the survey.

### Research instrument

The effectiveness of chatbots in the logistics industry was evaluated by a comprehensive survey instrument of 20 Likert-type items with responses ranging from 1 (expressing total disagreement) to 5 (indicating total agreement), coded $Q_1$ as $Q_{20}$, detailed in table 1, and designed to capture multiple dimensions of customer satisfaction. The survey, which used a 5-point Likert scale, focused on analyzing crucial aspects of chatbot performance. These aspects included ease of use, speed and quality of responses provided by chatbots, knowledge about products and services, problem-solving ability, language and grammar, and recommendation to other users. Each of these elements was carefully selected to obtain a comprehensive and accurate view of the customer experience in interaction with chatbots in the logistics industry.

**Table 1**
*Set of Likert type variables*

| Code | Definition |
|---|---|
| $Q_1$ | The chatbot was effective to meet my request |
| $Q_2$ | It was easy to interact with the chatbot |
| $Q_3$ | The chatbot provided me with timely answers |
| $Q_4$ | The chatbot provided me with accurate answers |
| $Q_5$ | The chatbot could solve my problem |
| $Q_6$ | The chatbot exceeded my expectations |
| $Q_7$ | The chatbot knew about the company's products/services |
| $Q_8$ | The chatbot could understand my problem |
| $Q_9$ | The chatbot saved me time compared to other support options |
| $Q_{10}$ | The chatbot was reliable |
| $Q_{11}$ | The chatbot was able to customize the interaction |
| $Q_{12}$ | The chatbot could anticipate my needs |
| $Q_{13}$ | The chatbot could empathize with my situation |


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| Code | Definition |
|---|---|
| $Q_{14}$ | The chatbot could handle my problem without transferring me to a human agent |
| $Q_{15}$ | The chatbot language was clear and easy to understand |
| $Q_{16}$ | Chatbot responses were grammatically correct |
| $Q_{17}$ | Chatbot tone was appropriate for interaction |
| $Q_{18}$ | The chatbot responses were concise |
| $Q_{19}$ | The chatbot was able to provide several options to solve my problem |
| $Q_{20}$ | I would recommend other people to use the chatbot |

This study used a 20-item Likert questionnaire, the result of a thorough consideration of the multiple dimensions that affect customer satisfaction with chatbots in logistics. Each item was selected for its relevance in measuring crucial aspects of the customer experience.

Ease of use, assessed by the accessibility and friendliness of the interface, seeks to address the user experience. The speed and quality of responses measure both the operational efficiency of the chatbot and the accuracy of its interactions. The assessment of product and service knowledge focuses on determining whether the chatbot has enough information to provide useful and accurate answers. Problem solving ability measures the effectiveness of the chatbot to address and solve problems autonomously. The evaluation of language and grammar focuses on the clarity and grammatical correctness of the answers, crucial aspects for the understanding and satisfaction of the user. Finally, the recommendation to other users provides a direct measure of customer satisfaction.

In addition, to enrich the analysis, relevant demographic information was collected from participants, including variables such as age, gender and educational level. This was done to identify possible patterns or variations in customer satisfaction related to these demographic characteristics.

This questionnaire was specifically designed to capture the complexities of interaction between users and chatbots in the logistics industry, carefully considering the elements that most impact consumer compliance. The formulation of the research hypothesis is based on the premise that the effectiveness of chatbots in this context is significantly influenced by key variables, such as the ability to solve problems, knowledge about products and services, autonomous problem management, grammatically correct responses and positive recommendations, all of them contributing directly to customer satisfaction.

Thus, considering all the information presented above, it is possible to propose the following research hypothesis:

The effectiveness of chatbots in the logistics sector is significantly influenced by key variables, such as the ability to solve problems, knowledge about products and services, autonomous problem management, grammatically correct responses and positive recommendations, directly impacting customer satisfaction.

## Data analysis

The data collected was analyzed using the latest version of R Studio statistical software (2023.06.0+421) to explore the correlation between customer satisfaction and the use of chatbots. Descriptive statistics, such as mean scores, standard deviations, and frequencies, were used to provide an overview of the data distribution. In addition, bivariate correlations were carried out to examine the relationships between individual variables. A multiple regression analysis was performed to identify significant factors affecting customer satisfaction.

The structure of the model is the following:

$$y = \beta_0 + \sum_{i=1}^{19} \beta_i \, x_1 + \varepsilon$$

Where:

Y: dependent variable (the chatbot was effective to meet my requirement)

$\beta_0$: the intercept

$\beta_0 \ldots \beta_{19}$: regression coefficients for independent variables

$x_2 \ldots x_{20}$: independent variables

$\varepsilon$: error term or model residuals

In this process, the most statistically significant predictors were carefully selected, which structured the adjusted final model. All tests necessary to demonstrate the validity of the model were carried out, setting a significance level of 0.05 (p-value) for all statistical tests. This rigorous methodological approach allows for a deep understanding of the relationships between variables and provides reliable and robust results to support the conclusions of the study.

## Results and discussion

### Descriptive analysis of information

Regarding the *gender* variable, there is a slight predominance of the male gender with a presence of 50.8%, and 3.04% of respondents responded as "other". In relation to the *age* variable, the groups are relatively proportional, highlighting the group of 31 to 40 years (29.28%), being 51 to 60 years the least representative (22%). Regarding the variable *education*, the participation of people with university education predominates (46.16%), over those with master's level education (32.96%), with the group with secondary education being the least representative (20.88%).

The relationship between the age of the client and the use of chatbots can provide valuable information to adapt and improve the implementation of these technologies, ensuring their efficiency and satisfaction in a wide range of users. Generations vary in familiarity and comfort with technology. Researching how different age groups adopt and use chatbots can provide valuable insights into the overall acceptance of this technology in society.

In our case, the minimum age of the client is 21 years, the maximum 60 years and the average 40.15 years, and it turns out that, if we consider three age groups (390 clients from 21 to 33 years; 491 clients from 24 to 47 years and 369 clients from 48 to 60 years), it is revealed that the demographic most willing to use chatbots is the one between 24 and 47 years. Surprisingly, it was also detected that the older group has a percentage of use very similar to that of the younger ones, challenging in this case, the paradigm that older people reject the use of technological tools.

Table 2 presents the main statistical descriptors of the sociodemographic variables. The most significant variability corresponds to the age variable, with a lower dispersion in the *gender* variable. All the variables considered have a negative kurtosis coefficient, indicating distributions that are platycurtic, i.e., with little concentration of data around the mean. The distribution of the *age* variable data is slightly biased to the right, and the *gender* and *education* variables have small negative asymmetry coefficients, indicating a not very pronounced asymmetry to the left.

**Table 2**
*Statistics on socio-demographic data*

| Variable | Average | Median | Standard deviation | Variance | Mode | Kurtosis | Asymmetry |
|---|---|---|---|---|---|---|---|
| Age | 40.153 | 40.00 | 11,119 | 126,632 | 37.00 | -1.054 | 0.067 |
| Education | 2.121 | 2.00 | 0.724 | 0.73 | 2.00 | -1.081 | -0.187 |
| Gender | 0.509 | 1.00 | 0.500 | 0.73 | 1.00 | -1.999 | -0.035 |

Regarding the correlations between sociodemographic variables, there is a moderate positive relationship between age and education. By contrast, the relationship between education and gender, as well as *age* and *gender* variables, is fragile and virtually null.

No respondents selected option 1 (strongly disagree) for any of the survey questions. The


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variable in the question $Q_9$ obtained the highest percentage in option 4 (agree) with 66.0 %. The variables $Q_{17}$ and $Q_{18}$, followed with 62.0 % and 56.0 %, respectively. The variable $Q_6$ recorded the highest percentage under option 2 (disagree) at 22 %. The variable $Q_2$ received the highest rate in option 5 (totally disagree) with 32 %, followed by the variable $Q_{13}$ with 30.0 %.

Table 3 presents the main statistical descriptors of the survey data. The variable has the highest mean (4.08), while the variable has the lowest mean (3.22). The highest data variability corresponds to the question, and the lowest data dispersion is observed in the question. In addition, all the variables considered have a positive kurtosis coefficient, indicating leptocurtic distributions with a strong concentration of data around the mean. The variables associated with the questions $Q_3$, $Q_4$, $Q_5$, $Q_6$, $Q_{12}$, $Q_{16}$, and $Q_{19}$ have a positive asymmetry coefficient; most observations are grouped to the left of the average value (values below the mean). In contrast, the other variables present a negative asymmetry coefficient, indicating that most observations are concentrated to the right of the average value (values above the mean).

**Table 3**

*Statistics of Likert type variables*

| Code | Median | Variance | Mode | Kurtosis | Asymmetry |
|---|---|---|---|---|---|
| Q1 | 4.00 | 0.619 | 4.0 | 2,604 | -0.071 |
| Q2 | 4.00 | 0,973 | 4.0 | 2,398 | -0.594 |
| Q3 | 4.00 | 0,571 | 3.0 | 2,520 | 0.022 |
| Q4 | 3.50 | 0.493 | 3.0 | 2,577 | 0.414 |
| Q5 | 4.00 | 0,526 | 3.0 | 2,442 | 0.374 |
| Q6 | 3.00 | 0,828 | 3.0 | 2,400 | 0.363 |
| Q7 | 4.00 | 0.545 | 4.0 | 2,468 | -0.048 |
| Q8 | 4.00 | 0,547 | 4.0 | 2,601 | -0.206 |
| Q9 | 4.00 | 0.402 | 4.0 | 3,816 | -0.413 |
| Q10 | 4.00 | 0.547 | 4.0 | 2,601 | -0.206 |
| Q11 | 4.00 | 0.844 | 4.0 | 2,427 | -0.422 |
| Q12 | 4.00 | 0.555 | 3.0 | 2,335 | 0.325 |
| Q13 | 4.00 | 0,606 | 4.0 | 2,331 | -0.643 |
| Q14 | 4.00 | 0.529 | 4.0 | 2,751 | -0.254 |
| Q15 | 4.00 | 0.890 | 4.0 | 2,120 | -0.193 |
| Q16 | 3.00 | 0.827 | 3.0 | 3,630 | 0.514 |
| Q17 | 4.00 | 0.665 | 4.0 | 2,048 | -0.324 |
| Q18 | 4.00 | 0.751 | 4.0 | 3,057 | -0.405 |
| Q19 | 4.00 | 0.771 | 4.0 | 2,198 | 0.160 |
| Q20 | 4.00 | 0.822 | 4.0 | 2,514 | -0.197 |

## Multiple linear regression analysis

The Cronbach coefficient, which evaluates the internal coherence of the elements of a scale, reveals the homogeneity of those elements, indicating that they all are oriented in the same direction (Taber, 2018). This coefficient, with a value of 0.92, is considered high, thus ensuring the reliability of the scale used (Doval *et al.*, 2023). In addition, the KMO (Kaiser-Meyer-Olkin coefficient), with a result of 0.82, indicates that the sample size was suitable for analysis.

The analysis of the relationship between variables is crucial to develop a multiple regression model, revealing the intensity and orientation of the connections between independent and dependent variables. This process provides insights into the structure of data and the interconnection of variables, as well as it prevents problems such as multicollinearity, caused by high correlations between independent variables. Understanding these relationships guides decisions about which variables to include in the model, improving its accuracy and effectiveness. This informed approach facilitates the construction of regression models for predictions and support in decision making.

In our case, after applying Pearson's method to obtain the respective correlations, it is relevant to mention the following:

- All correlations obtained are positive.
- The highest correlation value (0.75) occurs between variables $Q_1$ and $Q_{20}$
- The lowest correlation value (0.04) occurs between variables $Q_8$ and $Q_{20.}$

Using the general model, which contains all the variables as predictors, we obtain a determination coefficient $R^2$ value of 0.7877, which explains 78.77% of the variance, and a p-value of $9.9 \times 10^{-6}$. The choice of the most significant predictors was made by means of the Akaike measure (AIC), a process that after 13 steps confirmed that the variables $Q_5$, $Q_7$, $Q_{14}$, $Q_{16}$ and $Q_{20}$ are the best predictors, obtaining a value of 0.7512, which explains 75.12% of the variance and a p-value of $2.9 \times 10^{-12}$. Table 4 summarizes the information on the adjusted model coefficients.

**Table 4**

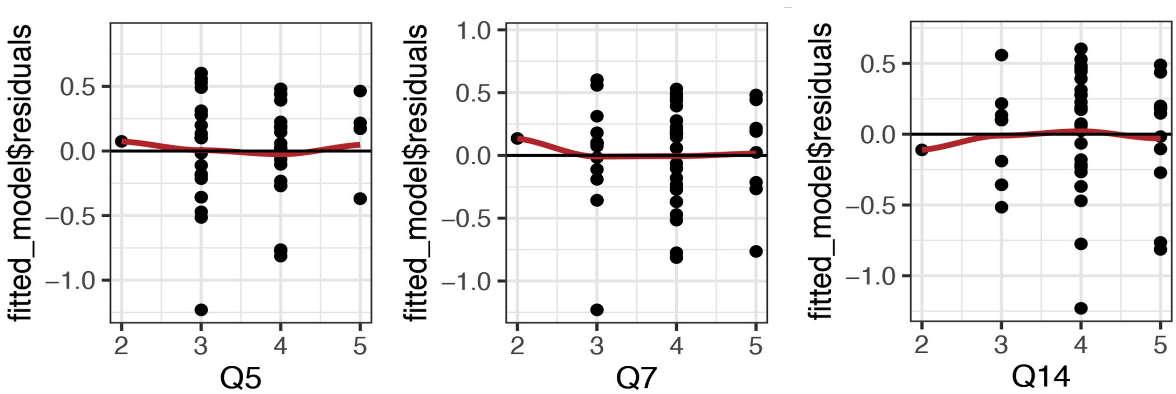
*Adjusted model coefficients*

| Intercept | Q5 | Q7 | Q14 | Q16 | Q20 |
|---|---|---|---|---|---|
| 0.2747 | -0.2381 | 4923 | -0.2119 | 0.2908 | 0.5419 |

To validate the linear association between the predictors and the dependent variable, the scattering diagram between each predictor and the residuals of the fitted model was generated (see figure 1). In addition, Shapiro-Wilks normality test was performed, which yielded a W statistic of 0.94329 and a p-value of 0.01822.

**Figure 1**

*Scatter Graph - Fitted Model*



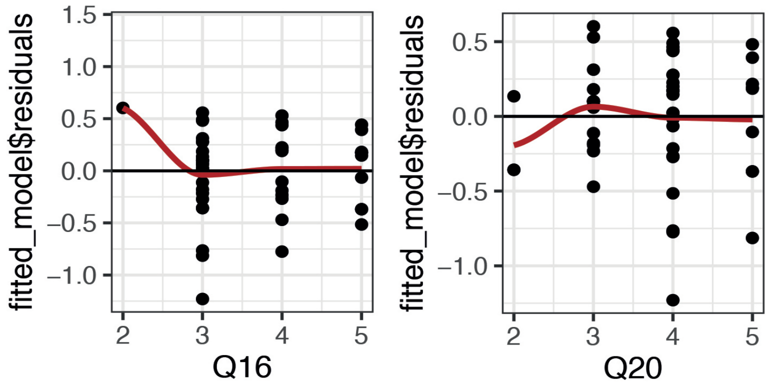
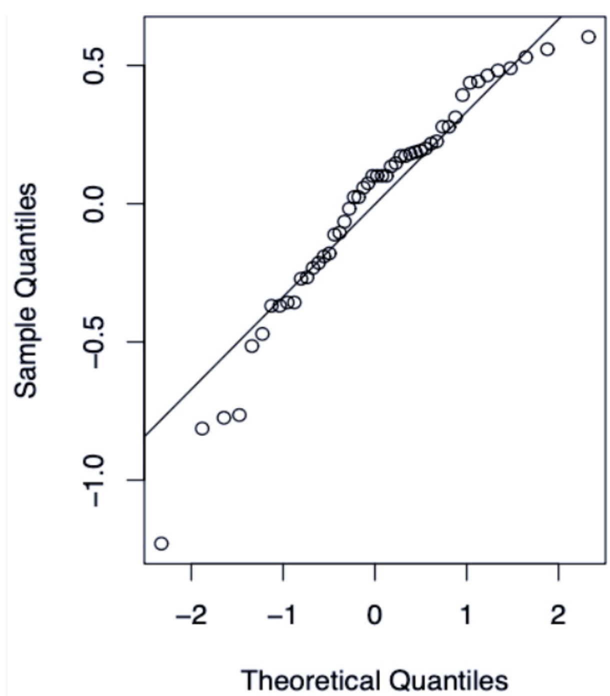



Figure 2 shows the Gaussian distribution of residues for the fitted model.

**Figure 2**
*Normality in waste distribution – adjusted model*



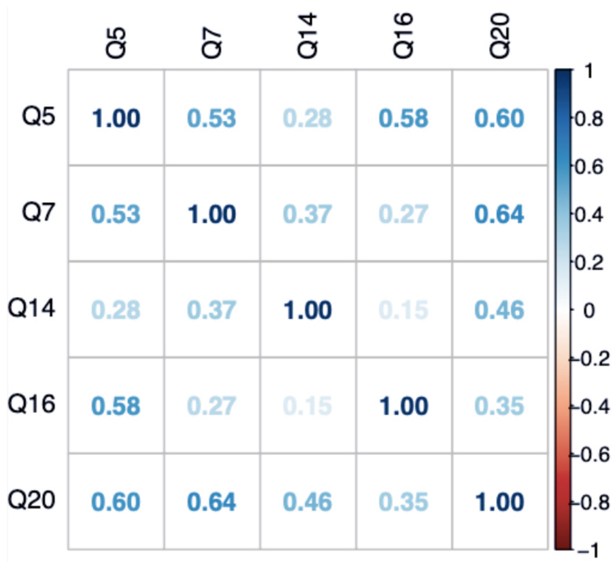

Subsequently, the standardized Breusch-Pagan test was applied, obtaining a BP statistic of 4.7853 with five degrees of freedom and a p-value of 0.4426.

After obtaining the correlation matrix between the predictors for the adjusted model (see Figure 3), it is essential to observe the following:

- All correlations obtained are positive.
- The highest correlation value (0.64) occurs between variables $Q_7$ and $Q_{20}$.
- The lowest correlation value (0.15) occurs between variables $Q_{14}$ and $Q_{16}$.

**Figure 3**

*Correlation matrix-adjusted model*




Inflation analysis of variance (IVF), and Durbin-Watson autocorrelation tests were carried out to identify possible evidence of inflation or linear correlation between predictors (see tables 5 and 6).

**Table 5**

*Inflation analysis of variance*

| $Q_5$ | $Q_7$ | $Q_{14}$ | $Q_{16}$ | $Q_{20}$ |
|---|---|---|---|---|
| 2.19167 | 1.83323 | 1.28585 | 1.52427 | 2.21194 |

**Table 6**

*Durbin-Watson Test Results*

| Delay | Autocorrelation | DW Statistician | p-value | $Q_{20}$ |
|---|---|---|---|---|
| 1 | 0.09125 | 1.76743 | 0.41 | 2.21194 |

In conclusion, the adjusted multiple linear model has the following structure:

$$Q_1 = 0.2747 - (0.2381)Q_5 + (0.4923)Q_7 - (0.2119)Q_{14} + (0.2908)Q_{16} + (0.5419)Q_{20}$$

The general model, which included the 19 variables as predictors, has a high value of 0.7877; it can explain 78.77% of the observed variability in the effectiveness of chatbots. The p-value of this model is significant ($9.9 \times 10^{-6}$), suggesting that the model is not random; at least one of the partial regression coefficients shows disparity with the value 0. These results indicate that the model as a whole has statistical relevance.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The adjusted model, which included only the variables $Q_5$, $Q_7$, $Q_{14}$, $Q_{16}$ and $Q_{20}$, has a $R^2$ greater value of 0.7229; it can explain 72.29% of the observed variability in the effectiveness of chatbots (only 6.58% less than the general model). The p-value of this model is significant ($2.9 \times 10^{-12}$). From the logistic perspective, the adjusted model suggests that the five selected variables have a stronger relationship with the effectiveness of chatbots compared to the other variables. Hence, the results indicate that factors such as the ability to solve customers' problems, knowledge of products/services, problem management without transferring to a human agent, grammatically correct answers and general recommendations are especially relevant in the logistical context.

The Shapiro–Wilks normality test is used to evaluate whether a data sample likely comes from a normally distributed population (King & Eckersly, 2019). The test produces a statistic and a p-value; in our case, the SW statistic is 0.94329; this value varies between 0 and 1, being the values closest to 1 an indicator of a better adherence to normality. The p-value of the test is 0.018, suggesting that the data are not perfectly distributed in a normal way, since the p-value is less than 0.05. However, this does not necessarily mean that the data are highly non-normal, as the test statistic of 0.94329 indicates that the deviation from normal is relatively small. The interpretation of the results may also depend on the specific context and assumptions of the statistical analysis.

The Breusch–Pagan test looks for a correlation between residue variances and a specific set of predictor variables (Raza *et al*., 2023). The test compares the null hypothesis, which postulates that there is no such relationship, with the alternative hypothesis that predictor variables influence variances of residues parametrically. This test can be carried out by an auxiliary regression, in which explanatory variables suspected of causing heteroskedasticity are used to square the residues back to the proposed model (Klein *et al*., 2016). The test yielded a BP statistic of 4.7853 and a p-value of 0.4426, suggesting that residue variability remains constant, this being a desirable property for such a model. This means that the variability of residues is consistent across the range of values of the independent variables, and the model predictions are equally accurate regardless of the level of the predictor variables. Therefore, there is no evidence of lack of homoscedasticity.

Inflation analysis of variance (IVF) identifies and quantifies multicollinearity in a multiple regression model. Multicollinearity occurs when two or more predictor variables in a regression model are highly correlated, which can lead to problems with model interpretation and affect the accuracy of estimates of regression coefficients. A IVF value of 1 indicates no multicollinearity, while values greater than 1 indicate increasing levels of multicollinearity (Senaviratna and Cooray, 2019). Our analysis of the IVF reveals that there is no evidence of multicollinearity in the adjusted model, since all inflation variability indices are below the limit of 3, ensuring that the predictor variables do not present high correlations, thus preserving the stability and interpretability of the model.

The Durbin–Watson test indicates that no autocorrelation test is observed in the residues of the fitted model (DW statistic = 1.76743, p-value = 0.41). Autocorrelation occurs when residues of a regression model are correlated, which violates the assumption of independence from errors. Autocorrelation can lead to biased and inefficient estimates of coefficients and reduce the reliability of model predictions (Dubin, 1988).

In regression analysis, Cook's distance is used to detect observations that exert a significant influence that may disproportionately affect estimated regression coefficients. We found no observations with a Cook distance greater than 1. Therefore, no significant value affects the model estimates (Espinheira and Oliveira Silva, 2020).

The highly competitive logistics industry has seen in chatbots a solution to differentiate itself in customer satisfaction. These programs, based on natural language processing (NLP) and artificial intelligence (AI), improve the relationship with consumers and reduce the workload of the employee. This study has provided an in-depth and evidence-based insight into the relationship between the use of chatbots in the customer service of logistics companies in the CPE area and their effectiveness related to customer satisfaction. The results obtained support the hypothesis raised in this research.

The results of the rigorous statistical analysis reinforce the notion that chatbots play a crucial role in improving customer service in the logistics sector. The significant and positive correlation between the use of chatbots and customer satisfaction highlights the ability of these systems to be a valuable tool in optimizing the customer experience. Key aspects, such as the effective solution of challenges, knowledge of inputs and services, responsiveness without human intervention, the use of precise grammar in responses and a strong reputation for customer satisfaction, were revealed as determining factors in the effectiveness of chatbots. By focusing on these factors, logistics companies can design more effective chatbots that more accurately meet their customers' demands and expectations.

The Cronbach and Kaiser-Meyer-Olkin indices highlight the internal consistency of the questionnaire scale and the robustness of the sample, supporting the robustness of the results achieved in the evaluation of the chatbots data.

The linear regression approach with multiple variables is effective, explaining the variability in chatbot effectiveness and showing linear relationships supported by scatter charts. This tool optimizes the strategic implementation of chatbots to improve customer service.

Although the observations did not perfectly fit a normal or Gaussian type distribution, the observed deviations are minor and do not significantly affect the interpretation of the results. The constant variability of the residuals suggests an appropriate fit of the model, but future research could explore the impact of sample dimension and distribution on model accuracy.

The multiple linear regression model suggests that the effectiveness of virtual assistants in customer support of logistics companies in the CPE zone is positively related to the chatbot's ability to solve customer problems, its knowledge about the company's products/services, its ability to handle problems without transferring them to a human agent, its grammatically correct responses, and its general recommendations to others. Interestingly, some of the variables that were not included in the adjusted model, such as $Q_3$ (timely responses) and $Q_9$ (time savings), had a lower impact on chatbot effectiveness. This suggests that customers can prioritize other aspects of chatbot performance over response time or time savings.

These findings are consistent with previous research on the influence of customer satisfaction with chatbots (Nicolescu and Turodache, 2022; Jenneboer *et al*., 2022, Um *et al*., 2020; Wetzel and Hofmann, 2020; Yun and Park, 2022; Haseeb *et al*., 2019; Tran *et al*., 2021; Tan and Liew, 2022, Fan *et al*., 2023) and suggest that customers can prioritize other aspects of chatbot performance over response time or time savings.

## Conclusion

Although the findings of this research indicate that the implementation of chatbots in customer service can achieve a favorable impact on consumer satisfaction, it is important to recognize the limitations of this study such as geographical limitation and concentration in logistics companies. Future research could explore the loyalty and retention of customers, the quality of chatbot responses, the personalization of interactions, and the optimal balance between chatbot and human support. In addition, future studies could increase the size of the sample and the diversity of companies for a wider generalization of the results and additional aspects could be explored from the logistic perspective, such as the personalization of interactions and the optimal balance between chatbot and human support, for a more complete and generalizable understanding in the logistics field.

The implications of this study extend beyond the confirmation of the hypothesis, offering valuable perspectives for the practical application of chatbots in logistics customer service. Future research could explore additional aspects, the quality of chatbot responses in emotionally or highly specialized situations, and the optimal balance between chatbot and human support.

In conclusion, this study reinforces the idea that the use of chatbots in the customer service of logistics companies in the CPE area is positively related to customer satisfaction. It provides a solid framework for strategic decision making in the implementation of chatbots, highlighting key areas that logistics companies can focus on to improve the effectiveness of their chatbots and ultimately the satisfaction of their customers.

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