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Are Chatbots the Key to Success in Customer Service for Logistics Companies? A Statistical Study of 10 of the Most Important Companies in South America

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ABSTRACT

This article aims to investigate the effectiveness of chatbots in improving customer service for logistics companies, focusing on ten of the most important companies in South America. Data was collected from 1250 chatbot users across these companies and analyzed to determine the relationship between chatbot usage and customer satisfaction. The results indicate that chatbots can effectively improve customer service in the logistics industry, with a significant positive correlation between chatbot usage and customer satisfaction. The study employed multiple regression analysis to identify the most important factors influencing customer satisfaction with chatbots, including the chatbot's capacity to address customer concerns, its familiarity with the company's products and services, its capability to manage issues without requiring human intervention, its usage of correct grammar in its responses, and its general reputation for customer satisfaction. The results of this study have important implications for the logistics industry, as they provide insight into the potential benefits of chatbot technology for enhancing customer service.

Keywords: *chatbots, customer satisfaction, customer service, multiple regression analysis, technology investment*

1. INTRODUCTION

The logistics industry plays a crucial role in global trade, enabling the movement of goods from producers to consumers across different regions. To ensure that this complex process runs smoothly, logistics companies must provide efficient and reliable customer service to their clients. In recent years, chatbots have emerged as a promising technology for improving customer service in the logistics sector.

Chatbots are computer programs that use artificial intelligence (AI) to simulate human conversations. They can provide 24/7 customer assistance without human intervention, making them an attractive option for logistics companies that want to offer round-the-clock support to their clients. Chatbots can provide information on order status, shipping details, and delivery times, among other things, helping to reduce customer wait times and improve customer satisfaction (Nicolescu and Tudorache, 2022).

The logistics sector is highly competitive, and companies constantly look for ways to differentiate themselves and improve customer service. As such, chatbots have become increasingly popular in the industry, with many companies adopting them to improve their customer service offerings (Jenneboer *et al.*, 2022). However, the effectiveness of chatbots in the logistics sector has yet to be extensively studied, and there is a need to assess their impact on customer satisfaction, response time, and issue resolution (Um and Chung, 2020). The relevance of this study lies in the market to provide efficient and reliable customer service in the logistics sector. Customers demand timely and accurate information about their orders, and logistics companies must be able to provide this information to maintain customer loyalty and satisfaction. Chatbots offer a potential solution to these challenges, but it is essential to assess their effectiveness in the logistics sector context (Wetzel and Hofmann, 2020).

This study aims to analyze the effectiveness of chatbots in customer service in the logistics sector. Specifically, the study aims to assess the impact of chatbots on customer satisfaction, response time, and the ability to resolve customer issues. The study will also identify the strengths and limitations of chatbots and provide recommendations for their effective implementation in the logistics sector.

The logistics sector encompasses the processes involved in moving and storing goods from producers to consumers. Artificial intelligence refers to the ability of computers to perform tasks that typically require human intelligence, such as natural language processing Customer satisfaction encompasses the extent of contentment a customer experiences in relation to a company's products or services. Meanwhile, response time denotes the duration it necessitates for a company to address and reply to inquiries made by its customers (Uvet, 2020). Issue resolution refers to the ability of a company to resolve customer issues effectively. Technology implementation refers to the process of integrating new technologies into an organization's operations (Haseeb *et al*., 2019).

In addition to improving customer satisfaction, chatbots can reduce company operational costs. A study by Jenneboer *et al*. (2022) found that adopting chatbots across the retail, banking, and healthcare sectors will realize business cost savings of $11 billion annually by 2023, up from an estimated $6 billion in 2018 by reducing labor costs. Alike, Um and Chung (2020) indicate that at chatbot's IBM Company can handle up to 80% of routine customer inquiries, freeing human customer service representatives to handle more complex questions.

However, despite these benefits, previous research has also identified several limitations and challenges in using chatbots in customer service. One of the primary limitations is the ability of chatbots to understand and respond to natural language (Smith, 2018). As mentioned in the previous section, chat- bots may need help understanding the context of a customer's inquiry leading to misunderstandings and frustration (Jenneboer *et al.*, 2022, Martins De Andrade and Tumelero, 2022). This limitation may be particularly significant in logistics, where customers may have complex and nuanced inquiries (Smith, 2018).

Another challenge is ongoing maintenance and updates to the chatbot's programming. As customer inquiries and preferences change over time, the chatbot must be updated to reflect these changes. This requires ongoing investment in time and resources to ensure the chatbot remains effective. Additionally, as the chatbot becomes more sophisticated, the risk of errors and misunderstandings increases, potentially leading to negative customer experiences. For instance, IBM (2020) suggests an intelligent conversational agent system architecture for e-commerce sales and marketing customer services. A pilot implementation of a chatbot for customer services is reported in a women's intimate apparel manufacturing firm. The proposed system includes emerging technologies such as web crawling, natural language processing, knowledge bases, and artificial intelligence. A prototype system is built and evaluated in a real-world setting. The system prototype evaluation results are satisfactory, supporting the system's effectiveness. The study also discusses implementation challenges and lessons learned, as well as the theoretical and managerial implications of the study.

In summary, this study aims to investigate the effectiveness of chatbots in the logistics sector and their impact on customer satisfaction, response time, and issue resolution. This research is crucial to understanding how logistics companies can improve customer service and maintain a competitive edge in the industry. This study will provide valuable insights into implementing chatbots in logistics by identifying their strengths and limitations and assessing their impact on key customer service metrics. Overall, the study will enhance customer satisfaction and help logistics companies offer more efficient and reliable customer service.

2. LITERATURE REVIEW

The logistics industry is pivotal in the global trade and commerce landscape. With the exponential growth of e-commerce, the sector is under mounting pressure to provide efficient and effective customer service. In response, logistics companies are leveraging various technologies to meet these demands, including using chatbots in customer service (Caldarini *et al.*, 2019). Chatbots are computer programs designed to simulate human conversation, providing a human-like experience to users. They can handle simple and repetitive tasks, answer frequently asked questions, and resolve issues in real-time. However, the extent to which chatbots effectively enhance customer service in the logistics industry remains to be seen and requires further research.

2.1 Use of Chatbots in Customer Service

The use of chatbots is on the rise as an increasingly popular tool in customer service for businesses of all sizes and industries. Chatbots are a form of artificial intelligence (AI) technology that enable companies to interact with customers in a personalized and efficient manner. Chatbots are computer programs designed to simulate human conversations and give users a human-like experience. **Figure 1** shows the number of research publications from Scopus, from 1970 to 2021 for the keyword "chatbot" (Caldarini *et al*., 2019).

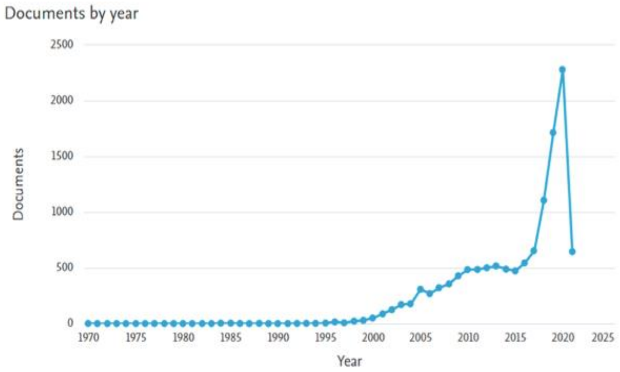

Figure 1 Research publications from Scopus, from 1970 to 2021 for the keyword "chatbot"

In the logistics industry, chatbots can provide a cost-effective and efficient way to handle customer inquiries and complaints. Logistics companies increasingly rely on chatbots to offer 24/7 customer support, improve response times, and reduce customer wait times. Chatbots can also handle simple and repetitive tasks, such as tracking orders, scheduling deliveries, and answering frequently asked questions (Davenport *et al*., 2020).

The use of chatbots in customer service can provide several benefits for logistics companies. Firstly, chatbots can simultaneously handle a high volume of customer inquiries, making it easier for companies to manage their customer support operations. They can also provide quick and accurate responses to customer inquiries, reducing response time and improving customer satisfaction. Moreover, chatbots can offer cost savings by reducing the need for human customer service representatives, who are more expensive to hire and train.

Chatbots can be integrated into various communication channels, including websites, messaging applications, and social media. This makes them easily accessible and convenient for customers, who can receive support through their preferred communication method (Illescas-Manzano *et al*., 2021). Additionally, chatbots can be programmed to understand natural language processing, meaning that they can handle a range of customer inquiries and respond human-likely (Ridha and Haura Maharani, 2022).

However, the quality of chatbot responses may depend on the data quality and algorithms used to train the chatbot (Sarker, 2021). If the data used to prepare the chatbot does not represent the customer population, the chatbot may not be able to handle all customer inquiries effectively (Trappey *et al*., 2020). The algorithms used to train the chatbot must also be carefully designed to ensure that the chatbot can handle a range of customer inquiries accurately; if they may not be able to handle complex issues or understand specific nuances of customer inquiries, customers may become frustrated and dissatisfied with the service provided by the chatbot (Adamopolou and Moussiades, 2020). Moreover, customers may prefer human interaction in some situations, such as when dealing with sensitive issues or complex tasks (Xu *et al.*, 2020).

Despite these limitations, using chatbots in customer service can improve customer satisfaction and reduce customer wait times in the logistics industry. Furthermore, using chatbots can provide cost savings for logistics companies, making it an attractive solution for customer service support. As AI technology expands in the logistics industry, chatbots will likely become an increasingly important tool for logistics companies to manage customer support operations (Toorajipour *et al.*, 2021).

2.2 Challenges and Limitations of Chatbots in Customer Service

While chatbots offer numerous benefits to logistics companies, several challenges and limitations must be considered. These challenges include technological limitations, customer preferences, and ethical concerns.

Mageira *et al.* (2022) identifies that one of the primary technological limitations of chatbots is their ability to understand and respond to natural language. While chatbots can be programmed to recognize and respond to specific phrases and keywords, they may need help understanding the context of a customer's inquiry or conversation. Last indicated can lead to misunderstandings and frustration on the part of the customer, potentially damaging the customer's perception of the company.

Another challenge is established by Marjerison *et al.* (2022), expressing the need for ongoing maintenance and updates to the chatbot's programming. As customer inquiries and preferences change over time, the chatbot must be updated to reflect these changes. This requires ongoing investment in time and resources to ensure the chatbot remains effective.

Customer preferences also present a challenge for chatbots in customer service. While some customers may prefer the convenience and efficiency of chatbots, others may prefer human interaction. Customers may be more comfortable speaking with a human representative when they require complex or sensitive assistance. Therefore, companies must consider the balance between chatbot and human support in their customer service operations (Hudiyono, 2022).

Table 1 provides an overview of the principal difficulties commonly encountered by chatbots when used in logistics customer service contexts. These challenges include the chatbots' inability to understand and respond to complex queries, their limited capacity to handle emotionally charged interactions and difficulties with natural language processing. Moreover, chatbots may face challenges when integrating with existing systems, particularly regarding multilingual support and managing complex business rules.

Table 1 Main common challenges faced by chatbots in logistic customer service

Challenge	Description	Example
Understanding complex queries	Chatbots may struggle to understand and provide a relevant response to complex customer queries or unusual terminology	Customers ask about the logistic of transportation of fragile or hazardous materials
Handling emotional interactions	Chatbots may not be able to provide empathetic responses in emotional customer service interaction	Customer express frustration over a delayed package
Multilingual support	Chatbots may not be able to understand or respond in multiple languages or dialects	The customer requests information in a language other than English
Integration with existing systems	Chatbots need to integrate with existing logistics systems to provide accurate and timely information to customers	Chatbot can't access the inventory management system to provide up-to-date tracking information
Data security and privacy	Chatbots need to be designed with data security and privacy in mind to protect sensitive customer information	Chatbot sends sensitive customer information over an unsecured network
Maintaining accuracy and relevance	Chatbots need to be updated regularly to ensure that they provide accurate and relevant information to customers	Chatbot provides outdated or incorrect information to a customer

The limitations of chatbots to meet these challenges can significantly affect their performance in logistics customer service, potentially leading to dissatisfied customers and damaging brand reputation. **Table 2** presents an overview of the constraints encountered by chatbots when employed in logistics customer service settings. These limitations include chatbots' inability to handle complex or creative queries, difficulties processing natural language, and challenges associated with emotionally charged interactions. Additionally, chatbots may face limitations related to multilingual support and integration with other systems and platforms and difficulties in managing complex business rules. Such restrictions can significantly impact the effectiveness of chatbots in logistics customer service, potentially leading to negative customer experiences and damage to a company's reputation.

Table 2 Main limitations faced by chatbots in logistic customer service

Challenge	Description	Example
Inability to handle complex or creative queries	Chatbots may not be able to understand and respond to complex or creative queries that go beyond their programmed capabilities	Customers ask for recommendations on products based on their personal preferences and past purchases
Difficulty handling emotionally charged situations	Chatbots may struggle to provide empathetic responses in emotionally charged situations, such as when a customer is upset or angry	The customer is angry about a lost or damaged package and is looking for an immediate resolution
Limited ability to handle natural language processing	Chatbots may not be able to handle the complexities of natural language processing and may not be able to understand differences in meaning	The customer uses sarcasm or humor in their query, which the chatbot fails to recognize
Challenges with multilingual support	Chatbots may struggle to understand and respond in multiple languages or dialects, which can limit their usefulness in global logistics customer service	The customer requests information in a language other than English that the chatbot is not programmed to understand
Difficulty with other platforms	Difficulty integrating with other systems or platforms	Chatbot can't access the inventory management system to provide up-to-date tracking information
Limitations in handling complex business rules	Chatbots may struggle to handle complex business rules that vary depending on the situation or location	Chatbot requests information about delivery options that vary depending on the destination

Ethical concerns also arise with the use of chatbots in customer service. For example, chatbots must be programmed to protect customer privacy and maintain confidentiality (Khanum and Mustafa, 2022). Additionally, companies must consider the potential for chatbots to perpetuate biases or discriminate against specific customers based on their language or background. To address these concerns, companies must carefully design and monitor their chatbots to ensure they operate ethically and equitably (Brendel *et al*., 2022).

Furthermore, the adoption of chatbots in customer service may be a variety of solutions (Caldarini *et al*., 2019; Zhang *et al*., 2021). Chatbots may not be suitable for all types of customer inquiries, and companies must assess the types of queries they receive to determine whether chatbots can effectively address them (Mohd Rahim *et al*., 2022). For example, complex inquiries or customer complaints may require human interaction to resolve satisfactorily.

In conclusion, while chatbots significantly benefit logistics companies in improving customer ser- vice and reducing costs, they also present several challenges and limitations that must be considered. Technological limitations, customer preferences, and ethical concerns all present potential barriers to successfully adopting chatbots in customer service. Therefore, companies must carefully evaluate the appropriateness of chatbots for their specific customer service needs and ensure that they are designed and implemented ethically and effectively.

2.3 Previous Research on the Effectiveness of Chatbots in Customer Service

Previous research has examined the effectiveness of chatbots in customer service across a variety of industries, including retail (Jones and Comfort, 2022; Rese *et al*., 2020; Tran *et al*., 2021; Kwangsawad and Jattamart, 2022; Jiang *et al*., 2022; Tan and Liew, 2022; Fan *et al*., 2023), healthcare (Mierzwa *et al*., 2019; Bates, 2019; Vaidyam *et al*., 2019; Abd-Alrazaq *et al*., 2020; Almalki and Azeez, 2020; Calvaresi *et al*., 2021; Rathnayaka *et al*., 2022; Puspitasari *et al*., 2022), tourism (Pillai and Sivathanu, 2020; Ivanov, 2020; Zhang *et al*., 2020; Rafiq *et al*., 2022; Pereira *et al*., 2022; Jones and Comfort, 2022) and finance (Adhim and Mulyono, 2023; Hwang and Kim, 2021; OECD, 2021; Alt *et al*., 2021; Nguyen *et al*., 2021; Jang *et al*., 2021; Lappeman *et al*., 2022). Ho and Chow (2023) measures the effectiveness of AI-Enabled chatbots in Customer Service using AnyLogic Simulation, through scenario analysis provides managerial implications for the average time in the system, response rate, satisfaction level, and cost savings, helping the companies to understand the impact of adopting AI-enabled chatbots in their customer service.

Several studies have shown that chatbots can improve customer satisfaction by quickly and conveniently responding to customer inquiries. For example, a study conducted by Ho and Chow (2023) found that the usability of chatbots positively affects extrinsic values associated with customer experience. In contrast, chatbot responsiveness positively impacts intrinsic matters related to customer experience. Furthermore, online customer experience positively correlates with customer satisfaction, and personality characteristics moderate the relationship between chatbot usability and extrinsic values of customer experience. Similarly, a study by Sung *et al*. (2022) found that the evolution of AI cognitive maturity in a Brazilian Commercial Bank allowed for 181 million interactions and 7.6 million attendances in 2020, resulting in enhanced service efficiency through gains in agility, availability, accessibility, resoluteness, predictability, and transhipment capacity. The chatbot service significantly reduced call and relationship centres' queues, enabling human attendants to focus on more complex attendances.

Previous research has also highlighted the importance of transparency and accountability in using chatbots in customer service. Chatbots must be programmed to protect customer privacy and maintain confidentiality, and companies must ensure that their chatbots operate ethically and equitably. Følstad *et al*. (2018) presents an interview-based research study to address the knowledge gap regarding the factors influencing users' trust in chatbots for customer service. The findings reveal that users' trust is influenced by factors related to the chatbot itself, including the quality of its interpretation of requests and advice, human likeness, self-presentation, and professional appearance. Additionally, users' trust is also influenced by contextual factors, such as the chatbot host's brand, the chatbot's perceived security and privacy, and general risk perceptions related to the requested topic. In any case, companies must ensure that customers are aware when they are interacting with a chatbot and when they are interacting with a human representative.

Finally, previous research has suggested that the effectiveness of chatbots may depend on the type of inquiry or customer interaction. While chatbots may be effective for routine questions and basic information requests, they may not be suitable for more complex or sensitive interactions. Companies must, therefore, carefully assess the types of inquiries they receive to determine whether chatbots can effectively address them. A study conducted by Følstad and Skjuve (2019) showed that infrequent insufficient responses from chatbots might not result in negative user experiences, provided the chatbot offers a straightforward method for connecting with human customer service representatives. This contrasted with the current literature on user perceptions of conversational agents. The study's participants exhibited practical expectations of chatbots' abilities, and while chatbots' human-like qualities may impact user experience, their capacity to handle inquiries effectively and appropriately is far more significant.

In conclusion, previous research has demonstrated the potential benefits of chatbots in customer service, including improved customer satisfaction and operational efficiency. However, using chatbots in customer service also presents several limitations and challenges, including the ability to understand and respond to natural language, the need for ongoing maintenance and updates, and the importance of ethical considerations and transparency. Therefore, companies must carefully evaluate the appropriateness of chatbots for their specific customer service needs and ensure that they are designed and implemented effectively and ethically Bang *et al*. (2021). In conclusion, while chatbots significantly benefit logistics companies in improving customer service and reducing costs, they also present several challenges and limitations that must be considered. Technological limitations, customer preferences, and ethical concerns all present potential barriers to successfully adopting chatbots in customer service. Therefore, companies must carefully evaluate the appropriateness of chatbots for their specific customer service needs and ensure that they are designed and implemented ethically and effectively.

3. MATERIALS AND METHODS

3.1 Participants

The current study recruited 1250 participants, customers of 10 prominent logistics companies operating in South America. Participants were selected through targeted email invitations sent to customers who had used chatbot services within the preceding six months. All participants were volunteers and provided informed consent before completing the survey.

3.2 Measures

The effectiveness of chatbots in the logistics industry was assessed through a comprehensive survey instrument designed to capture multiple dimensions of customer satisfaction. The survey consisted of 20 items, measured on a 5-point Likert scale, which assessed key aspects of chatbot performance, including ease of use, speed of responses, quality of answers, and overall usefulness. Additionally, the survey gathered relevant demographic information such as age, gender, and educational level.

3.3 Data Analysis

To determine the correlation between customer satisfaction and chatbot usage, the collected data was analysed using the advanced statistical software R Studio. Descriptive statistics were calculated to provide an overview of the data distribution, including mean scores, standard deviations, and frequencies. Bivariate correlations were computed to explore the relationship between individual variables. Multiple regression analysis was used to identify the most significant factors influencing customer satisfaction with chatbots. A significance level of p-value of 0.05 was employed for all statistical tests.

In summary, the current study employed a rigorous methodology to assess the effectiveness of chatbots in improving customer service within the logistics industry. The survey instrument was designed to capture a broad range of customer experiences. Advanced statistical techniques enabled us to identify critical factors influencing customer satisfaction with chatbot services.

4. RESULTS

4.1 Descriptive Analysis of Data

The sample for this study corresponds to the answers of 1250 participants, customers of the ten most important logistics companies in South America, except Brazil. The data set consists of 23 variables divided into two groups. The first group contains three socio-demographic variables (see **Table 3**). The second group corresponds to a survey of 20 questions, coded from Q1 to Q20; these questions are Likert-type with responses from 1 (strongly disagree) to 5 (strongly agree).

Table 3 Socio-demographic variables

Name	Definition
Age	Customer age
Education	Customer educational level: 1 (high school), 2 (college), 3 (master's degree)
Gender	Customer gender: 0 (female), 1 (male), 2 (other)

Figure 2 shows the design for the three socio-demographic variables. It can be concluded that for the gender variable, there is a slight predominance of the male gender with 50.8% presence and that 3.04% of the respondents answered as "other", referring to their gender. Regarding the age variable, in general, the four age groups considered turned out to be relatively proportional; we can

see that the most crucial group corresponds to 31-40 years surveyed with 29.28%, being the group of 51-60 years the least representative with 22% presence. For the education variable, there is a predominance of college education level participants with 46.16% presence over those master's degree education level with 32.96%, being the group of high school education level the least representative with 20.88% presence.

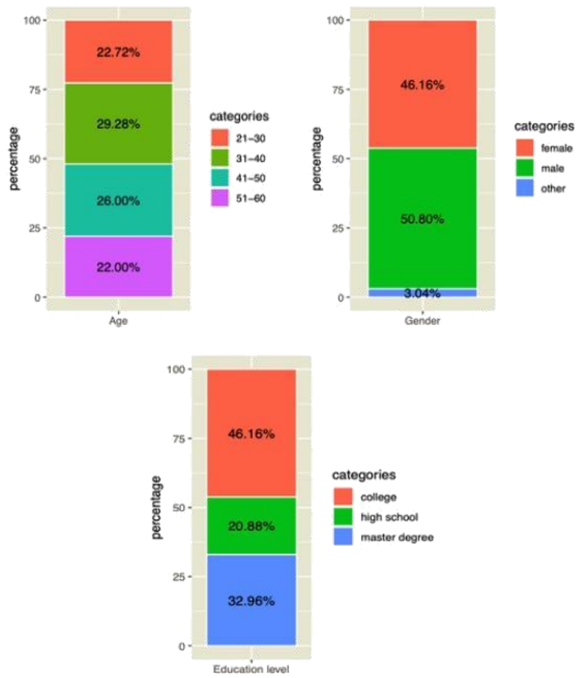

Figure 2 Structure of socio-demographic variables

Table 4 shows the main statistical descriptors of socio-demographic variables, being relevant that the greatest variability of data belongs to the age variable and the least dispersion of data for the gender variable. Additionally, all considered variables have a negative coefficient of Kurtosis, meaning that their distributions are of a platykurtic type, with little concentration of data around the mean. The data's distribution of age variable is slightly skewed to the right, and the variables gender, education have small negative coefficients of skewness, indicating that their skewness is not very pronounced to the left.

Table 4 Descriptive statistics for the socio-demographic variables

	Mean	Median	Std. Dev.	Variance	MFV	Kurtosis	Skewness
Age	40.153	40.00	11.119	126.632	37.00	-1.054	0.067
Education	2.121	2.00	0.724	0.524	2.00	-1.081	-0.187
Gender	0.509	1.00	0.500	0.250	1.00	-1.999	-0.035

Table 5 shows the correlations between the socio demographic variables, it can be observed that age and education variables are moderately positively related, while the relationship between age and college variables, as well as between the gender and gender variables is very weak and practically null.

Table 5 Correlations for the socio-demographic variables

	Age	Education	Gender
Age	1.000	0.174	0.016
Education	0.174	1.000	0.018
Gender	0.016	0.018	0.100

The set of variables for the multiple linear regression analysis correspond to the 20 Likert-type questions with answers from 1 (strongly disagree) to 5 (strongly agree), coded from Q1 to Q20, included in the survey, as shown in **Table 6**.

Table 6 Set of variables

Variable code	Definition
Q_1	The chatbot was effective in attending to my requirement
Q_2	The chatbot was easy to interact with
Q_3	The chatbot provided me with timely responses
Q_4	The chatbot provided me with accurate responses
Q_5	The chatbot was able to solve my issue
Q_6	The chatbot was able to solve my issue
Q_7	The chatbot was knowledgeable about the company's products/services
Q_8	The chatbot was able to understand my issue
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 personalize the interaction
Q_{12}	The chatbot was able to anticipate my needs
Q_{13}	The chatbot was able to empathize with my situation
Q_{14}	The chatbot was able to handle my issue without transferring me to a human agent
Q_{15}	The chatbot's language was clear and easy to understand
Q_{16}	The chatbot's responses were grammatically correct
Q_{17}	The chatbot's tone was appropriate for the interaction
Q_{18}	The chatbot's responses were concise and to the point
Q_{19}	The chatbot was able to provide me with multiple options to resolve my issue
Q_{20}	I would recommend the chatbot to others

Table 7 shows the mean, standard deviation, and response percentage for the survey questions from Q1 to Q20 and for each of the five options. Notably, absolutely none of the surveyed responded with 1 (totally disagree) to any of the survey questions. Question Q9 (The chatbot saved me time compared to other support options) variable obtained the highest percentage in option 4 (agree), with 66.0%. Variable Q9 is followed by variables Q17 (The chatbot's tone was appropriate for the interaction) and Q18 (The chatbot's responses were concise and to the point) with 62.0% and 56.0%, respectively. The Q6 (The chatbot exceeded my expectations) variable obtained the highest percentage in option 2 (disagree) with 22%. The Q2 (The chatbot was easy to interact with) variable received the highest rate in option 5 (totally agree) with 32% followed by variable Q13 (The chatbot was able to empathize with my situation) with 30.0%.

Table 7 Set of variables

Variable code	Mean (SD)	Option 2(%)	Option 3(%)	Option 4(%)	Option 5(%)
Q_1	3.56 (0.79)	8.0	38	44.0	10.0
Q_2	3.92 (0.99)	12.0	16.0	40.0	32.0
Q_3	3.60 (0.76)	4.0	44.0	40.0	12.0
Q_4	3.58 (0.70)	2.0	48.0	40.0	10.0
Q_5	3.62 (0.73)	2.0	46.0	40.0	12.0
Q_6	3.22 (0.91)	22.0	44.0	24.0	10.0
Q_7	3.84 (0.74)	2.0	30.0	50.0	18.0
Q_8	3.94 (0.74)	2.0	24.0	52.0	22.0
Q_9	3.92 (0.63)	2.0	18.0	66.0	14.0
Q_{10}	3.94 (0.74)	2.0	24.0	52.0	22.0
Q_{11}	3.82 (0.92)	10.0	22.0	44.0	24.0
Q_{12}	3.66 (0.75)	2.0	44.0	40.0	14.0
Q_{13}	4.08 (0.78)	4.0	14.0	52.0	30.0

Table 7 Set of variables (Con't)

Variable code	Mean (SD)	Option 2(%)	Option 3(%)	Option 4(%)	Option 5(%)
Q_{14}	3.96 (0.73)	2.0	22.0	54.0	22.0
Q_{15}	3.74 (0.94)	10.0	30.0	36.0	24.0
Q_{16}	3.64 (0.83)	2.0	52.0	26.0	20.0
Q_{17}	3.92 (0.67)	2.0	20.0	62.0	16.0
Q_{18}	3.74 (0.75)	6.0	26.0	56.0	12.0
Q_{19}	3.76 (0.77)	2.0	38.0	42.0	18.0
Q_{20}	3.76 (0.82)	6.0	30.0	46.0	18.0

Table 8 shows the primary statistical descriptors of the survey data. Q13 (The chatbot was able to empathize with my situation) is the variable with the highest mean (4.08), and Q6 is the variable with the lowest mean (3.22). The highest data variability belongs to question Q2 and the lowest dispersion of data for question Q9. In addition, all the variables considered have a positive Kurtosis coefficient; their distributions are leptokurtic, with a large concentration of data around the mean. The variables corresponding to questions Q3, Q4, Q5, Q6, Q12, Q16, and Q19 have a positive skewness coefficient; most of its data are clustered to the left of the mean (values less than the mean). In contrast, the other variables have a negative skewness coefficient; most of its data are clustered to the right of the mean (values greater than the mean).

Table 8 Descriptive statistics for the likert survey variables

Variable code	Median	Variance	MFV	Kurtosis	Skewness
Q_1	4.00	0.619	4.0	2.604	-0.071
Q_2	4.00	0.973	4.0	2.398	-0.594
Q_3	4.00	0.571	3.0	2.520	0.022
Q_4	3.50	0.493	3.0	2.577	0.414
Q_5	4.00	0.526	3.0	2.442	0.374
Q_6	3.00	0.828	3.0	2.400	0.363
Q_7	4.00	0.545	4.0	2.468	-0.048
Q_8	4.00	0.547	4.0	2.601	-0.206
Q_9	4.00	0.402	4.0	3.816	-0.413
Q_{10}	4.00	0.547	4.0	2.601	-0.206
Q_{11}	4.00	0.844	4.0	2.427	-0.422
Q_{12}	4.00	0.555	3.0	2.335	0.325
Q_{13}	4.00	0.606	4.0	2.331	-0.643
Q_{14}	4.00	0.529	4.0	2.751	-0.254
Q_{15}	4.00	0.890	4.0	2.120	-0.193
Q_{16}	3.00	0.827	3.0	3.630	0.514
Q_{17}	4.00	0.665	4.0	2.048	-0.324
Q_{18}	4.00	0.751	4.0	3.057	-0.405
Q_{19}	4.00	0.771	4.0	2.198	0.160
Q_{20}	4.00	0.822	4.0	2.514	-0.197

When applying the Cronbach analysis to the survey data set, the results shown in **Table 9** were obtained. Cronbach's alpha is a measure of the internal consistency of the survey that makes it possible to demonstrate its homogeneity; that is, this coefficient allows us to measure the reliability of the statistical instrument. With the Chatbots data from the questionnaire, an alpha equal to 0.92 was obtained. This value represents an excellent level of internal consistency for the Likert scale.

The Guttman's value of $\lambda 6$, a measure of reliability obtained from the coefficient of determination of each survey item concerning the others and resulting in 0.95, is considered an outstanding value. The average correlation value between the items was 0.36, which indicates that, on average, they have a regular association with each other. Additionally, it is crucial to indicate that there are no missing responses, that is, no question was left unanswered, and that after analysing how the Cronbach's alpha would be affected by the removal of any question, it was determined that it's not necessary to remove any question to increase the value of the Cronbach index.

Table 9 Survey reliability data

Raw alpha	Std. alpha	$\lambda 6$ Guttman	Average r
0.92	0.92	0.95	0.36

When calculating the Kaiser-Meyer-Olkin (KMO) coefficient, a value of 0.82 was obtained. This value indicates that a significant proportion of the variance in the survey variables can be explained if a dimensional reduction is applied to the Chatbot data.

4.2 Multiple Linear Regression Analysis

4.2.1 Analysing the Relationship among Variables

Analysing the relationship among variables is crucial as the first step to developing a multiple regression model because it allows us to identify the strength and direction of the relationships between the independent and dependent variables. This information helps us understand the underlying structure of the data and how the different variables are related. It also allows to identify potential issues or challenges that may arise during the modelling process, such as multicollinearity, which occurs when independent variables are highly correlated. By understanding the relationships among the variables, we can make informed decisions about which variables to include in the model and how to interpret the results. Ultimately, this helps to build a more accurate and effective regression model that can be used to make predictions and inform decision-making timely, this helps to build a more accurate and effective regression model that can be used to make predictions and inform decision-making.

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

- All the correlations obtained are positive.
- The highest value of correlation (0.75) occurs between the variables Q1 (The chatbot was effective in attending to my requirement) and Q20 (I would recommend the chatbot to others).
- The lowest value of correlation (0.04) occurs between the variables Q8 (The chatbot was able to understand my issue) and Q13 (The chatbot was able to empathize with my situation).

4.2.2 Forming the Models

The structure or our model is the following:

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

where:

y: dependent variable Q_1 (The chatbot was effective in attending to my requirement)

β_0: the intercept

$\beta_1 \ldots \beta_{19}$: the regression coefficient for independent variables

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

ε: model's error term or residuals

4.2.3 Generating the Generalized Model

Using the mixed starting with the generalized model, containing all variables as predictors, we obtain the results summarized in **Table 10**.

Table 10 Summary generalized model

Model	R	R Square	Adjusted R Square	F-statistics	p-value
Generalized	0.4632	0.7877	0.6532	5.858 on 19 and 30 df	9.9×10^{-6}

The results obtained for the generalized model coefficients are shown in **Table 11**.

Table 11 Generalized model coefficients

	Estimate	Std. error	t value	Pr(>|t|)
Intercept	-0.330	0.762	-0.434	0.668
Q_2	-0.062	0.101	-0.618	0.541
Q_3	-0.050	0.149	-0.338	0.738
Q_4	0.157	0.141	1.114	0.274
Q_5	-0.217	0.169	-1.283	0.209
Q_6	-0.080	0.127	0.629	0.534
Q_7	0.556	0.150	3.713	0.001
Q_8	0.100	0.135	0.742	0.464
Q_9	0.019	0.171	0.113	0.910
Q_{10}	-0.127	0.120	-1.058	0.299
Q_{11}	0.012	0.098	0.119	0.906
Q_{12}	-0.034	0.146	-0.229	0.821
Q_{13}	0.051	0.143	0.359	0.722
Q_{14}	-0.207	0.133	-1.562	0.129
Q_{15}	-0.039	0.092	-0.422	0.676
Q_{16}	0.301	0.118	2.547	0.016
Q_{17}	0.137	0.131	1.045	0.304

Table 11 Generalized model coefficients (Con't)

	Estimate	Std. error	t value	Pr(>|t|)
Q_{18}	0.147	0.234	0.630	0.533
Q_{19}	0.111	0.147	0.076	0.940
Q_{20}	0.345	0.257	1.342	0.190

4.2.4 Generating the Fitted Model

The selection of the best predictors was made with the Akaike (AIC) measurement, a process that, after 13 steps, confirmed the variables Q5, Q7, Q14, Q16, and Q20 as the best predictors. **Table 12** illustrates the summary of the fitted model.

Table 12 Summary fitted model

Model	R	R Square	Adjusted R Square	F-statistics	p-value
Fitted	0.4141	0.7512	0.7229	26.57 on 5 and 44 df	2.87×10^{-12}

Table 13 summarizes the information on the coefficients of the fitted model.

Table 13 Fitted model coefficients

Intercept	Q_5	Q_7	Q_{14}	Q_{16}	Q_{20}
0.2748	-0.2382	0.4924	-0.2120	0.2909	0.5420

It is always advisable to obtain the confidence interval for each partial regression coefficient. **Table 14** provides this information.

Table 14 Fitted model's confidence interval

	2.5%	97.5%
Intercept	-0.5838	1.1332
Q_5	-0.4817	0.0054
Q_7	0.2737	0.7109
Q_{14}	-0.3978	-0.0261
Q_{16}	0.1128	0.4687
Q_{20}	0.3263	0.7576

4.2.5 Validation of Conditions for Multiple Linear Regression

To validate the linear relationship between the predictors and the response variable, the scatter diagram between each one of the predictors and the residuals of the fitted model was obtained, which is shown in **Figure 3**.

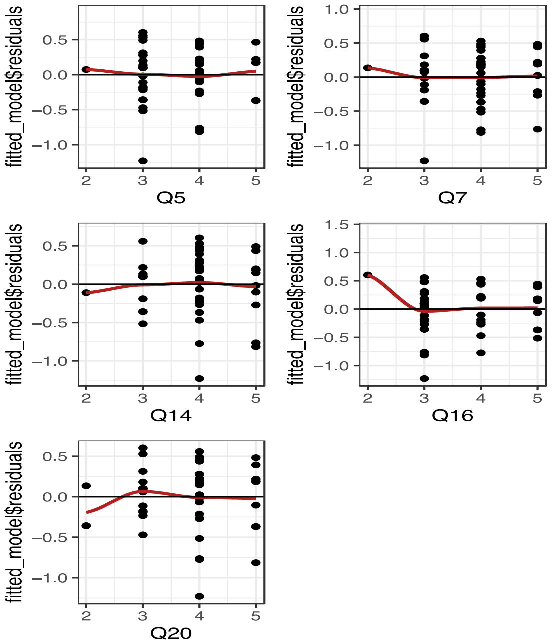

Figure 3 Scatter plot

Figure 4 shows the normal distributions of residuals for the fitted model.

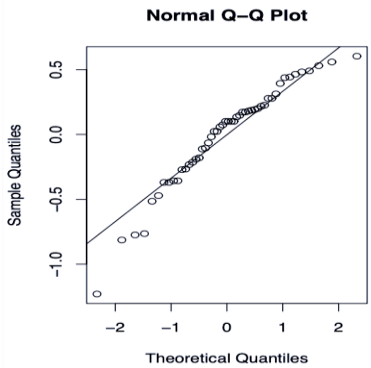

Figure 4 Normal distribution of residuals

Additionally, the Shapiro-Wilks normality test resulted in a W-statistics of 0.9433 and a p-value of 0.0182.

Regarding the constant variability of the residuals (homoscedasticity), **Figure 5** illustrates the representation of the residuals against the values fitted by the model to be able to observe a specific pattern.

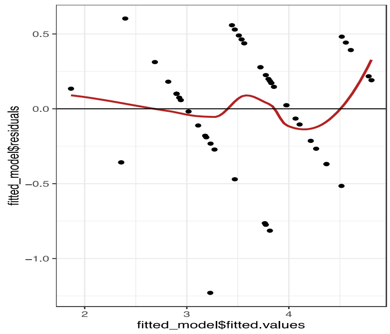

Figure 5 Residuals vs fitted values

Applying the Studentized Breusch-Pagan test, a BP-statistics of 4.7853 on five freedom grades and a p-value of 0.4426 was found.

After obtaining the correlation matrix between predictors for the fitted model (see **Figure 6**), it is important observe the following:

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

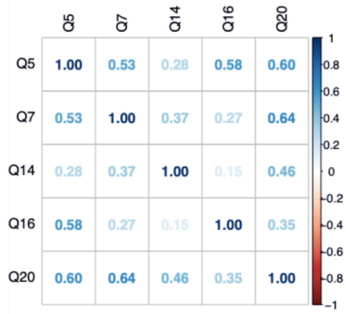

Figure 6 Correlation matrix

The variance inflation (VIF) analysis and Durbin-Watson Autocorrelation tests were completed to find evidence of inflation or linear correlation between the predictors. **Table 15** and **Table 16** allow us to observe the results obtained.

Table 15 Variance inflation analysis

Q_5	Q_7	Q_{14}	Q_{16}	Q_{20}
2.1917	1.8332	1.2859	1.5243	2.2119

Table 16 Durbin-Wattson autocorrelation test

Lag	Autocorrelation	DW-statistics	p-value
1	0.0913	1.7674	0.42

In conclusion, the fitted multiple linear models have the following structure:

$$Q_1 = 0.2748 - (0.2382)Q_5 + (0.4924)Q_7 - (0.2120)Q_{14} + (0.2909)Q_{15} + (0.5420)Q_{20} \quad (2)$$

5. DISCUSSION

Chatbots have gained popularity in recent years, particularly in the customer service industry. Logistics companies are no exception, as they face the challenge of managing many customer queries and complaints. This study aims to investigate whether chatbots are the key to success in customer service for logistics companies in South America. To accomplish the objective mentioned above, a multiple linear regression model was developed by utilizing data from a survey of 1250 individuals who were each presented with 20 Likert questions.

Cronbach's Alpha is a measure of internal consistency of the item that forms a scale that allows evidence of its homogeneity, that is, that the items are in the same direction (Raval, 2020), it turned out to be 0.92, which is considered high to guarantee the reliability of the scale used. The λ6 Gutman value, a measure of reliability obtained from the coefficient of determination of each item of the reactive concerning the others, is 0.95, which is a high value. The Kaiser-Meyer-Olkin measure of sampling adequacy (KMO) was 0.82, indicating that the sample size was sufficient for the analysis.

The generalized model, which included all 19 variables as predictors, has a high R^2-value of 0.788; it can explain 78.8% of the variability observed in the effectiveness of chatbots. The p-value of this model is significant ($9.92\ x\ 10^{-6}$) so it can be accepted that the model is not random; at least one of the partial regression coefficients is different from 0. Many of them are not significant, indicating that they might not contribute to the model. These results suggest that the overall model was statistically significant.

The fitted model, which included only the variables Q5, Q7, Q14, Q16, and Q20, has a higher R^2-value of 0.723; it can explain 72.3% of the variability observed in the effectiveness of chatbots (just 6.5 % less than the generalized model). The p-value of this model is significant ($2.87\ x\ 10^{-12}$). These results suggest that the selected variables have a stronger relationship with the dependent variable, Q1, than the other variables.

As regards the linear relationship between the predictors of the fitted model and the response variable, the scatter plots confirm the linear relationship since the residuals are randomly distributed around zero with practically constant variability along the X-axis. Therefore, linearity is fulfilled for all the predictors of the fitted model.

The Shapiro-Wilks normality test is a statistical test used to assess whether a sample of data will likely come from a normally distributed population (King and Eckersly, 2019). The test produces a test statistic and a p-value; in our case, the SW-statistics is 0.9433; this value ranges between 0 and 1, with values closer to 1 indicating better adherence to normality. The p-value of the test is 0.018, suggesting that the data is not perfectly normally distributed, as the p-value is less than 0.05. However, this does not necessarily mean that the data is highly non-normal, as the test statistic of

0.9433 indicates that the deviation from normality is relatively tiny. The interpretation of the results may also depend on the specific context and assumptions of the statistical analysis.

The Breusch-Pagan test aims to determine whether there is a relationship between the variances of the residuals and a specific set of explanatory variables. The test aims to compare the null hypothesis, which states that there is no such relationship, with the alternative hypothesis that the predictor variables influence the variances of the residuals in a parametric manner. This test can be conducted through an auxiliary regression, in which the explanatory variables suspected to cause heteroscedasticity are used to regress the squared residuals of the proposed model (Castillo *et al*., 2020). The test returned a BP- statistics of 4.785 and a p-value of 0.443, indicating that the variance of the residuals was constant, which is a desirable property for a linear regression model. This means that the variance of the residuals is consistent across the range of values of the independent variables, and the model's predictions are equally precise regardless of the level of the predictor variables. Therefore, there is no evidence of a lack of homoscedasticity.

The variance inflation is a method used to identify and quantify multicollinearity in a multiple regression model. Multicollinearity occurs when two or more predictor variables in a regression model are highly correlated. This can lead to problems with the interpretation of the model and can affect the accuracy of the estimates for the regression coefficients. The VIF is a measure of how much the variance of the estimated regression coefficient is increased due to multicollinearity in the model. Specifically, the VIF is the ratio of the variance of the coefficient estimate in a model that includes all the predictor variables to the variance of the coefficient estimate in a model that only consists of a single predictor variable. A VIF value of 1 indicates no multicollinearity, while values greater than 1 indicate increasing levels of multicollinearity (Wang *et al*., 2022). In our case, the Variance Inflation Factor (VIF) analysis suggests that there is no evidence of multicollinearity in the fitted model, as all the VIF values are well below the threshold of 3 (VIF values > 3). This means that the predictor variables are not highly correlated with each other, which is essential because multicollinearity can lead to unstable and unreliable estimates of the coefficients and reduce the interpretability of the model.

The Durbin-Watson test indicates no evidence of autocorrelation in the residuals of the fitted model (DW-statistics = 1.7674, p-value = 0.42). Autocorrelation occurs when the residuals of a regression model are correlated, which violates the assumption of independence of the errors. Autocorrelation can lead to biased and inefficient estimates of the coefficients and reduce the reliability of the model's predictions (Ngai *et al*., 2021).

Cook's distance is a measure used in regression analysis to identify influential observations that may disproportionately affect the estimated regression coefficients. Regarding the potential outliers or meaningful observations in the data, we found no observations with a Cook distance greater than 1. Therefore, no significant values affect the model estimates (Cook and Weisberg, 1982). However, it is essential to mention that removing observations 9, 27, and 390 did not significantly impact the coefficients' estimates or the model's goodness of fit, indicating that they could be more influential.

The results of this study suggest that chatbots can be effective in customer service for logistics companies in South America. The fitted model identified five variables that significantly impact the effectiveness of chatbots: Q5, Q7, Q14, Q16, and Q20. These variables relate to the chatbot's ability to solve customer issues, knowledge about the company's products/services, handle problems without transferring to a human agent, make grammatically correct responses, and overall recommendations to others.

Interestingly, some of the variables that were not included in the fitted model, such as Q3 (timely responses) and Q9 (timesaving), had a lower impact on the effectiveness of chatbots. The last suggests that customers may prioritize other aspects of chatbot performance over response time or timesaving.

The multiple linear regression model indicates a positive correlation between the effectiveness of chat- bots in customer service for logistics companies in South America and various factors. Specifically, the chatbot's ability to address customers' issues (Q5) aligns with findings from prior studies (Wetzel and Hofmann, 2020; Tran *et al*., 2021). Similarly, the integration of knowledge about the company's products and services (Q7) corresponds with observations in Tan and Liew (2022). Furthermore, providing accurate responses (Q14) is supported by evidence in Nicolescu and Tudorache (2022), Haseeb *et al*. (2019), Kwangsawad and Jattamart, (2022). The ease of understanding the chatbot (Q15) is consistent with outcomes reported in Jenneboer *et al*. (2022), Um and Chung (2020), Rese *et al*. (2020), Fan *et al*. (2023). Additionally, receiving positive recommendations from customers (Q20) aligns with the conclusions drawn in Jenneboer *et al.* (2022), Jiang *et al*. (2022). These congruencies emphasize the robustness and validity of our research outcomes, as they mirror and reinforce existing insights in the field.

While the findings of this study suggest that implementing chatbots in customer service can positively impact customer satisfaction, it is vital to acknowledge the limitations of this study. One limitation is that the study only surveyed customers in South America, so the results may need to be more generalizable to other regions. Additionally, the study only focused on logistics companies, so it is unclear if these findings can be applied to other industries.

Further research could explore the impact of chatbots on customer loyalty and retention. It would also be valuable to investigate how the quality of the chatbot's responses and the personalization of interactions impact customer satisfaction. Additionally, the research could explore the optimal balance between chatbot and human support in customer service interactions. Finally, future studies could expand the scope to include a larger sample size and a more diverse set of companies to increase the generalizability of the results.

6. CONCLUSIONS

The logistics industry is highly competitive, and customer service is a key differentiator. In recent years, chatbots have emerged as a potential solution to improve customer service in the logistics industry. Chatbots are computer programs that use natural language processing

(NLP) and artificial intelligence (AI) to communicate with customers conversationally. They can provide quick and efficient responses to customer inquiries, enhancing customer satisfaction and reducing the workload of human customer service agents.

The statistical analysis conducted in this study provides strong evidence of the effectiveness of chatbots in improving customer service in the logistics industry. The study found a significant positive correlation between chatbot usage and customer satisfaction, indicating that chatbots can be a valuable tool for improving customer service. The study also identified several key factors affecting chatbot effectiveness, including the ability to address customer concerns, knowledge of the company's products and services, capability to manage issues without human intervention, usage of correct grammar in its responses, and reputation for customer satisfaction. By focusing on these factors, logistics companies can develop more effective chatbots that better meet their customers' needs and expectations.

The multiple linear regression model utilized in this study proved highly effective. The high R^2 value indicates that the model can explain a significant proportion of the variability observed in chatbot effectiveness. The selected variables were shown to be more closely related to the dependent variable than other variables, and scatter plots confirmed a linear relationship between the predictors and the response variable. This model can be a valuable tool for logistics companies to optimize their chatbot implementation and improve customer service.

Although the data did not conform perfectly to a normal distribution, the deviations were relatively minor, and they may not significantly impact the interpretation of the results. Furthermore, the constant variance of the residuals suggests that the model was appropriate for the data. However, further research could explore the impact of sample size and distribution on the model's accuracy.

In conclusion, the statistical analysis conducted in this study provides valuable insights into the potential benefits of chatbot technology for enhancing customer service in the logistics industry. By implementing the factors identified in this study and utilizing the multiple linear regression model, logistics companies can develop more effective chatbots that better meet their customer's needs and expectations, resulting in improved customer service experiences. The use of chatbots can also reduce the workload of human customer service agents, allowing them to focus on more complex customer issues and improving their overall job satisfaction.

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