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Exploring Voice of Customers to Chatbot for Customer Service with Sentiment Analysis

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Abstract. *Chatbots have been widely employed across a wide variety of companies and industries, from small- and medium-sized businesses to large corporations, and from e-commerce to financial institutions. Although chatbots have proven to be far more efficient and quicker than human agents, they do not always provide customers with a satisfactory experience because they lack a personal touch. Customer issues are often left unresolved and many are unsatisfied with chatbot services. This is unfavorable for firms that use chatbots for customer services as this jeopardizes their relationship with valued consumers. Thus, customer input is essential to streamline the product innovation process. This study uses a hybrid method involving lexicon-based TextBlob and logistic regression techniques to identify the sentiments of consumers toward chatbots for customer services based on user-generated content on Twitter. The results show that although people generally have positive encounters with chatbots, the gap between positive and negative sentiments is relatively small. This research provides insights that businesses can use to improve chatbot technology based on the voice of the customer to provide users with higher quality customer services in the future, especially since unsatisfied customers could be a threat to a business's performance.*

Keywords: *Chatbot, customer services, sentiment analysis, social media mining, voice of customers.*

1. Introduction

The transformation of customer service interactions via chatbots, which assist enterprises in managing customer service experiences, is one of the most prominent applications of artificial intelligence (AI) (Murtarelli et al., 2021). A chatbot is a computer program that can converse with human users using natural language (Maudlin, 1994). The chatbot ecosystem is comprised of voice-driven digital assistants (e.g., Siri, Cortana, Alexa, and Google Home), as well as text-based systems deployed on instant messaging platforms (Sheehan et al., 2020).

The chatbot market is estimated to grow from $2.6 billion in 2019 to $9.4 billion by 2024, with chatbots in the customer service industry expected to be the fastest-growing market category between 2019 and 2026 (Nguyen, 2020). Over the previous decade, chat services have become the primary means of obtaining customer support (Charlton, 2013). Technological advancements in AI have allowed chatbots to handle increasingly complicated jobs thanks to their ability to use holistic thinking and provide context-specific responses (Huang & Rust, 2018). Many of the advantages that chatbots provide are related to increased efficiency, such as lower costs, shorter client wait times, and the increasing customer preference for digital rather than voice-based conversations (Shumanov, 2021).

In Indonesia, some of the largest banks have developed chatbots to provide customer support, such as Bank BRI's Sabrina, Bank BCA's Vira, and Bank BNI's Cinta. The telecommunications industry has also adopted the use of this technology, with Telkomsel's Veronika, XL's Maya, and Indosat's Indira (Katadata.co.id, 2018). In contrast, only two

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chatbots have been developed in the fast-moving consumer goods (FMCG) market: Jemma from Unilever and Shalma from Alfamart (Katadata.co.id, 2018). Chatbot technology is projected to be used for one-quarter of all customer care activities by 2020 (Moore, 2018). However, many users continue to have negative experiences with chatbots (e.g., high failure rates), which may make it difficult for customers to follow the chatbot's advice and requests (Adam et al., 2020). For example, chatbots may respond to user requests inappropriately, resulting in a disconnect between the user's expectations and the system's performance (Luger & Sellen, 2016). Customer service chatbots can only remain relevant and interesting if they provide a positive user experience and offer value propositions that encourage customers to contact them again (Folstad & Skjuve, 2019).

Chatbot developers and companies must first understand what customers expect from chatbots used as customer service agents in order for them to design responsive chatbots for customer service. With the expansion of social media, such as Twitter, user-generated content (UGC) has grown to be a significant source of information in which people discuss everything about the products they use, including their advantages and disadvantages. UGC thus provides a continuous high-quality source of product development information from users on various topics. Unlike crowdsourcing, this strategy does not struggle with the issue of sustaining a continuous supply of high-quality ideas over time because customers post their tweets on a daily basis. Businesses can benefit from this information and tailor their offerings to meet their customers' demands.

The substitution of human chat service agents with AI-based chatbots raises the question of whether live chat services will remain effective, as skepticism and resistance to the technology may block task fulfillment and prevent successful service interactions (Adam et al., 2020). Some research indicates that chatbots only have a 50% chance of achieving AI awareness by 2050 (Müller & Bostrom, 2016). Despite the numerous technological advancements in recent decades, there are still several potential directions for the development of chatbot technology (Arsovski et al., 2018).

Given the benefits and downsides of chatbots that have been discussed, there is an urgent need for product innovation in the context of chatbot technology. Hence, the following research questions will guide this study:

RQ1: What are the top keywords related to chatbots used for customer services according to UGC on Twitter?
RQ2: What is the overall sentiment toward chatbots used for customer service based on UGC on Twitter?

This study aims to use these two research questions to explore the top keywords related to, as well as to identify the overall sentiment toward, chatbots in customer services. The development of chatbots is driven by technology-push innovations. However, previous research has mostly focused on system architecture while neglecting the voices of customers. By understanding the main keywords associated with and the sentiment toward chatbots from customers on Twitter, this study aims to provide insights into how businesses can improve chatbot technology based on customer feedback to provide them with better quality customer support in the future, as unsatisfied customers are a threat to the business's performance. Therefore, this issue requires serious attention.

2. Literature Review / Hypothesis Development

Chatbots as Customer Service

The nature of service delivery has altered dramatically due to technological advancements. Many high-touch and low-tech customer service operations have been redesigned such that technology either complements or replaces human employees

(Wang, Harris, & Patterson, 2013). A chatbot is an intelligent agent that communicates with users using natural language processing and machine learning (Shumanov & Johnson, 2021). Although the origins of intelligent agent technology can be traced back to 1966 and ELIZA, an agent designed to understand natural language and communicate with users, advances in AI and neural network programming have led to a wide variety of applications, such as customer engagement, legal discovery, and knowledge management (Schneider, 2017).

As a self-service technology, chatbots can not only save money (Gnewuch et al., 2017) but also improve the quality of the service provided as well as provider-customer interactions (Adam et al., 2020). Studies have shown that, in the current climate, chatbots can save $1.3 trillion in global corporate expenditures associated with 265 billion customer support inquiries every year by reducing response times by 30%, freeing up people for other tasks, and answering up to 80% of all basic questions (Reddy, 2017).

Previous studies have shown that chatbot technology must still be improved because customers frequently experience unsatisfactory services compared to human agents (Table 1). We noticed an apparent knowledge gap in early studies on chatbots used in customer service, as these studies did not present a clear set of chatbot features that needed to be enhanced. Furthermore, little research has been conducted on chatbots that leverage social media mining for data collection. In general, past research on chatbots in customer services relied mostly on experiments conducted on small populations. In contrast, UGC on social media platforms represents a much wider dataset from individuals all around the world, making it highly advantageous for research purposes. UGC is expected to provide a broader view of the issue, and the outcomes are more likely to be relatable not only to people in a certain area but to individuals across the world. Hence, this study was conducted to close this knowledge gap.

Table 1.
Literature Review On Chatbots As A Customer Service.

Author	Methodology	Finding
Ngai et al., 2021	Qualitative Case study	Presents the system architecture in general terms by rigorously focusing on the features of the system structure. The designs described can effectively improve efficiency in handling customer queries and thus customer relationship management.
Chung et al., 2020	Quantitative Survey	Marketing activities did not have a substantial impact on communication skills, and so did not result in satisfactory outcomes. Participants may have assumed that the chatbot service was more capable than offline services. They thought chatbots were accurate and credible, even though they did not provide a wide range of information, efficiency, or time savings.
Tran et al., 2021	Quantitative Twitter-mining	Consumers often rated their experiences with chatbots higher than their contact with online human representatives. In addition, consumer sentiment toward online human agents became more negative after the implementation of chatbots.
Shumanov & Johnson, 2021	Quantitative Conversation-log analysis	Chatbots can be programmed to take on a personality using response language, and matching customers to similar chatbot personalities can increase customer interactions with chatbots while boosting financial outcomes for businesses.

Table 1. (Continued)
Literature Review On Chatbots As A Customer Service.

Author	Methodology	Finding
Song et al., 2022	Quantitative Situational experiment	Different types of service agents have a direct impact on a consumer's adoption intention, and consumers are more willing to accept human beings as service agents than chatbots. Furthermore, consumers have the perception that human beings have higher communication capabilities than chatbots.
Xu et al., 2020	Quantitative Field-based experiment	Customers believed that AI had stronger problem-solving capabilities and were more likely to choose that type of customer support for low-complexity activities.
Pantano & Pizzi, 2020	Quantitative Patent analysis	Indicated the current areas of development (as outlined by the number of patents) that might lead to the introduction of new chatbots.

User-Generated Content, the Voice of Customers, and Social Media Mining

UGC is created by ordinary individuals who willingly share data, information, or media on social media networks. The usage of such content has grown rapidly in recent years, partly because it is mostly free and easily accessible. Grover et al. (2019) stated that UGC can be used to clarify developing paradigms and uncover new patterns related to the area of study (Daim et al., 2016). UGC collected by social media mining has thus been widely accepted in the literature as a primary source of data for research purposes. UGC is also an excellent tool for amplifying the voice of customers (VOC). Individuals like to express their thoughts about everything from movies to political issues, especially on Twitter, because it triggers engagement and makes them feel connected with other users.

VOC is defined as a collection of customer needs and desires (Griffin & Hauser, 1993) or a description of customer preferences and aversions (Roman, 2010). VOC contains a significant amount of information that businesses can utilize in a variety of ways. For example, VOC provides comprehensive insights into the impressions that clients have of products and services. This information provides critical clues that can be used to identify client requirements, which may then be utilized to assess customer preferences and desires (Griffin & Hauser, 1993). VOC can also be used to identify essential areas for evaluation, such as the features of a product that customers value the most as well as those that require additional improvement (Manchulenko, 2001; Woodruff, 1997). VOC can also suggest strategic directions for the progression of a firm by providing a shared common language (Hauser, 1993; Kärkkäinen et al., 2001).

The easiest way to explore and learn about VOC is through social media. The rising use of social media platforms offers several potential advantages to businesses, including the ability to create improved products and services as well as serve their customers in novel ways (Kristensson et al., 2008). Almost 80% of business leaders consider social media to be a helpful tool for communicating with customers that have contributed to the success of their organization (Hennig-Thurau et al., 2010). In response to the rapidly increasing customer usage and interest in social media over the last decade, research projects that analyze UGC and provide quality intelligence have developed rapidly over the last decade (Bashir et al., 2017). This popular field of study is known as social media mining and it involves the gathering and analysis of social media data to extract useful and hidden information (Choi et al., 2020).

Researchers proposed social media mining as a means by which commercial enterprises could conduct product/service planning based on a thorough understanding of their clients, in which issues associated with customer needs and satisfaction measurement are investigated, product opportunities are identified, service quality and gaps are quantified, and customer-driven product technologies and functionalities are discovered (Choi et al., 2020). Because the manual examination of ideas published on internet platforms is an exceedingly time-consuming and costly operation, many studies have instead evaluated and classified the innovative ideas presented on online platforms (Ozcan et al., 2021).

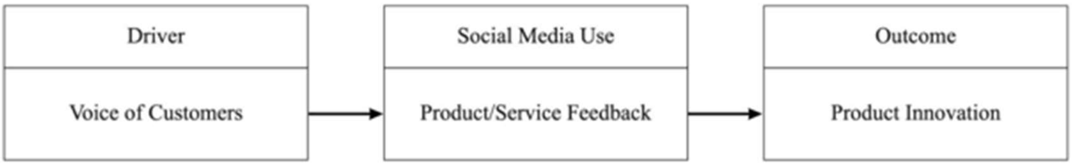

Figure 1.
Conceptual Framework Of The Research.

2. **Methodology**

The first step in this study was the extraction of data from UGC using the Twitter API. Tweets were gathered and processed to remove text-based noise using stopwords. Tokenization and lemmatization were also applied. Sentiment analysis was then performed on the cleaned dataset using TextBlob to identify the sentiment of each tweet.

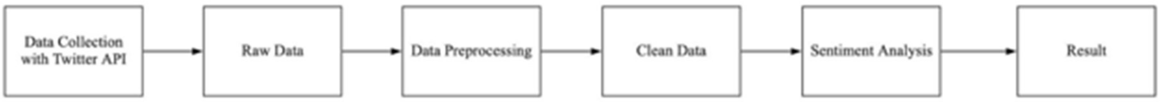

Figure 2.
Methodological Framework Of The Research.

Data Collection
According to Sibona et al. (2020), UGC is a legitimate source for the implementation of this data-mining approach. Twitter was chosen as the primary source for data collection in this study as we believe that tweets contain a significant amount of data. Mining this data can provide insights into public opinion and behavioral responses in specific scenarios (Chew & Eysenbach, 2010). In particular, Twitter serves as a customer services channel because it is easy and effective for businesses to offer direct and immediate support to customers and prospects. This involves monitoring and responding to customer tweets and creating a great customer experience that is visible to others on the platform. Another reason why Twitter was chosen as the main data source in this study is because of the benefits described by Pak and Paroubek (2010):

1. Many people utilize microblogging platforms to voice their ideas on various issues, making them an important source of people's opinions.
2. Twitter has a massive volume of text-based posts; this volume has continued to grow on a daily basis. The gathered corpus might be of any size.
3. Twitter's viewership includes everyone from normal users to celebrities, business leaders, politicians, and even country presidents. This allows for the collection of text posts from members of a wide variety of social groups.

4. Twitter's viewership is comprised of users from many countries.

The Twitter API was used to crawl tweets in April 2022 with keywords such as "customer service chatbot", "customer service chatbots", "customer service bot", "customer service bots", "chatbot AI", and "chatbots AI." We also eliminated retweets, replies, quotes, links, and hashtags from the query because our observation indicated that these features were frequently used by spam bots. This step was performed to ensure that the tweets gathered were of high quality and posted exclusively by customers. Additionally, the tweets were extracted in English. For ethical reasons, we only retrieved the tweets and posting dates (ranging from 8th–30th April 2022). Importantly, the Twitter API does not provide personal information, such as Twitter usernames, ensuring the anonymity of Twitter users. Furthermore, this study only analyzed the contents of each tweet, guaranteeing the confidentiality of the respondents.

Data Preprocessing

In text mining, noise is typically removed to improve the quality of the text and the consequent findings (Celardo et al., 2016). The preprocessing of the prepared data was divided into seven steps:

(1) Remove duplication.
(2) Transform contractions into their formal versions.
(3) Remove special characters or text noise.
(4) Change all text to lowercase.
(5) Tokenize the sentence by spaces.
(6) Lemmatize the words into their root forms.
(7) Remove common stopwords.

4,359 tweets were scraped in April 2022. However, only 4,063 tweets remained after duplicates were removed. We then transformed all contractions (e.g., don't, wouldn't, can't) into their formal counterparts (e.g., do not, would not, and cannot). Following that, special characters such as punctuation marks (e.g., !–%$#&?/.;") and numbers were removed from the dataset since they were not relevant to the text analysis. The text normalization process utilized the Python Regular Expression library (re), commonly known as RegEx. All characters were transformed to lowercase to ensure that the dataset was stored in a consistent format. Tweets were subsequently tokenized into individual words, and each given word was lemmatized to its root word. Finally, the stopwords library in the Natural Language ToolKit (NLTK) was used to remove irrelevant stop words (e.g., "I", "you", "the", and "a"), allowing for the analysis to focus only on the meaningful words.

Table 2.
Comparison Of The Raw Data To The Cleaned Data.

Raw Data	Clean Data
@118KB @virginmedia They are pretty useless. They told me to contact them via WhatsApp but that's just a ChatBot! They need British people to answer the phones, not transferred to Bangladesh call centres. I'm sure the people are lovely, but they don't understand a simple English question.	Pretty useless tell contact via whatsapp chatbot need british people answer phone transfer bangladesh call centre sure people lovely not understand simple english question
@ASOS is there a customer service email please? My wife is trying to get in touch but the live chat is a bot and doesn't understand what she is saying.	Customer service email please wife try get touch live chat bot not understand say

Table 2. (Continued)
Comparison Of The Raw Data To The Cleaned Data.

Raw Data	Clean Data
@FirstMediaCares I've called but only the bot answered, is this on purpose so that customers can't contact customer services directly?	Call only bot answer purpose customer contact customer service directly
@anteraja_id it's crazy that you gave the customer services phone number but it's not active. Even on WhatsApp, it's bot that answers, your Instagram comments section is closed. I suppose it's also bot that run your Twitter account. It's really not clear	crazy give customer service phone number not active whatsapp answer instagram comment section close suppose bot run twitter account really not clear

Data Analysis
Sentiment analysis algorithms are used to categorize and partition datasets into various groups. TextBlob is a Python library for Natural Language Processing (NLP) that is commonly used to analyze and handle substantial amounts of textual data and relies heavily on the NLTK to achieve its goals (Saura et al., 2021). NLTK is a library that allows for the easy categorization and classification of text-based datasets by offering quick access to many lexical resources. In this study, sentiment analysis was conducted by using TextBlob to determine the polarity scores of each tweet and classify them in terms of polarity or subjectivity. The sentiment function provides a polarity score between −1 and 1.

Tweets with polarity scores of less than 0 are considered negative, tweets with polarity scores equal to 0 are considered neutral, and tweets with polarity scores greater than 0 are considered positive. This metric is commonly used for the categorization of data in sentiment analysis (Saura et al., 2021). We used logistic regression to validate the results of our sentiment analysis using TextBlob by considering the precision, recall, f1-score, and support metrics of our data as described by Hiremath and Patil (2020).

4. Findings and Discussion

Word Cloud, Frequency, and Percentage
Query terms such as “chatbot”, “chatbots”, “bot”, “bots”, “customer”, “service”, and “AI” were excluded from the generation of the word cloud since these terms would naturally populate the finding. Figure 3 presents the most frequent keywords related to our main query in the form of a word cloud, while Table 3 lists the top 20 most frequent words in the dataset, revealing some intriguing preliminary findings.

> “No real time support from the care. The Chatbot asked me to send a mail to care team and it says will revert me back within 24-48hrs. Really!!!!!!!!”
> “Hi I urgently need customer support and can’t contact anyone. Let me know how to speak to someone. I have tried email and the support chatbot to no reply.”
> “Would be nice if i could get some one to actually respond to any of the help requests i've made to get access to my account.... instead all i get are bots that don't help one bit. Your customer service in 2022 is disgusting.”
> “I've been trying to reach your customer support since 3 days and there's no one to answer except a bot. How are we supposed to deal with issue with order if customer support is non existent?”

Several tweets suggest that many users complain to brand accounts on Twitter because they tried to contact the company's customer support, but were unable to resolve their problems using the chatbot representative, leaving them in desperate need of extra help.

Figure 3.
Word Cloud Of The Most Mentioned Keywords.

Table 3.
The Top 20 Keywords Arranged In Order Of Frequency.

Word	Freq	%	Word	Freq	%
get	730	1.17%	time	315	0.50%
support	539	0.86%	one	308	0.49%
use	503	0.81%	would	306	0.49%
help	500	0.80%	go	304	0.49%
chat	460	0.74%	say	288	0.46%
like	402	0.64%	account	274	0.44%
care	346	0.55%	word	270	0.43%
make	329	0.53%	need	270	0.43%
call	328	0.53%	people	262	0.42%
try	323	0.52%	contact	258	0.41%

Sentiment Analysis
We used a hybrid model that combined a TextBlob lexicon-based classifier with a classical logistic regression machine learning model to evaluate sentiment toward chatbots as a customer service on Twitter. We chose this hybrid strategy for two reasons. First, recent research has indicated that sentiment analysis should not be deployed as an "off-the-shelf" approach without modification (Ribeiro et al., 2016). Second, we were able to integrate the benefits of both lexicon-based and machine learning techniques, which leads to better outcomes (Dhaoui et al., 2017). Furthermore, by employing these methods, we were able to bypass the need for manual coding, which reduced the possibility of subjective coder bias.

Following sentiment analysis–conducted using TextBlob in Python–it was discovered that 1,594 (39.2%) tweets were categorized as positive, 1,285 (31.6%) tweets were identified as negative, and the remaining 1,183 (29.1%) tweets were classified as neutral. The distribution of positive, negative, and neutral posts in the collected data is presented in Figure 4. The number of positive posts outweighs the number of negative and neutral posts. Before the data preprocessing step, a logistic regression model was developed to validate the results of the sentiment analysis. The model has an accuracy of 0.78, which is relatively high because stopwords such as "no", "not", and "but" had not yet been removed from the dataset. This was done because, according to Sohangir et al. (2018), negative words are used to flip a sentence's polarity. Generally, variables such as accuracy, recall, f1-score, and support are presented with respect to the different sentiments identified in sentiment analysis. In this context, accuracy is a metric that assesses the fitness of the machine learning model. Thus, the statistical validity of the proposed sentiment analysis model increases as the accuracy score increases (Saura et al., 2021).

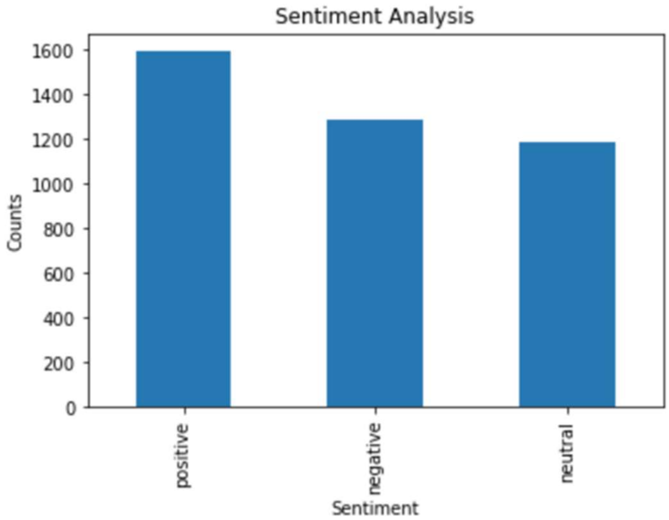

Figure 4.
Distribution of the sentiment with TextBlob.

Table 4.
Results From The Logistic Regression Model.

Parameters	Precision	Recall	F-1 Score	Support
Negative	0.71	0.78	0.74	246
Neutral	0.83	0.76	0.80	284
Positive	0.79	0.79	0.79	364
Accuracy			0.78	894
Macro avg.	0.78	0.78	0.78	894
Weighted avg.	0.78	0.78	0.78	894

According to UGC on Twitter, chatbots are still championed for their effectiveness in delivering positive experiences in the context of their interactions with customers. However, firms should pay serious attention to the growing negative sentiment regarding chatbots used for customer service since chatbots may have an impact on consumer expectations about service quality (Tran et al., 2021). One probable explanation for this trend is a chatbot's ability to appropriately address simple inquiries promptly. Past research has indicated that the escalating expectations of customers for speed and convenience have resulted in the increased deployment of self-service technologies (Collier & Kimes, 2013; Grewal et al., 2017). Furthermore, AI can outperform humans in simple, repetitive activities such as commonly requested queries (Huang & Rust, 2018; Xu et al., 2020). However, the gap between the proportion of positive and negative sentiment toward chatbots in customer services is relatively small, indicating that there are a growing number of unsatisfied customers who demands immediate attention from businesses with regard to enhancing the product or service quality of their chatbots.

5. Conclusion

This paper studied the results of the application of sentiment analysis techniques to Twitter data. Specifically, it used a hybrid model that involved an unsupervised lexicon-based TextBlob method as well as a supervised logistic regression method to classify 4,603 tweets related to chatbots in customer services. The word cloud illustrates the words that consumers often use when expressing their sentiments regarding their interactions with chatbots. The words “get”, “support”, “use”, “help”, and “chat” were among the top 20 most frequently used words. These terms are associated with customer experiences when engaging with chatbots that work as a brand's customer service. Some consumers tried using the chatbots to contact customer service but were unsuccessful; as a result, they took their complaints to Twitter instead.

The sentiment analysis results indicate that the positive sentiment toward chatbots used in customer service was higher than the negative and neutral sentiments. Sentiment analysis provides a good indicator of how pleased consumers are with a product or service. A significant amount of customer feedback is available on Twitter; hence, there is a strong need to rapidly analyze comments or sentences to identify customer sentiments. It is important to note that data without sentiment can be misleading. For example, a company may believe that its chatbot technology operates effectively based on the number of customers it serves each day because the chatbot outnumbers the performance of human agents in terms of quantity. This may lead the company to believe that they should continue using the chatbot for customer service purposes without upgrading it because they lack knowledge of what their consumers truly think or feel about it. However, this study shows that there is a rising trend in negative sentiments toward the use of chatbots in customer service. These findings are expected to prompt businesses to assess their technology and identify critical areas for product improvement so that chatbots can better serve customers in the future.

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