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RESEARCH ARTICLE

# Customer Dissatisfaction Towards Chatbot Services of e-Commerce Shopping Sites: A Qualitative Analysis

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**ABSTRACT**
This research examines the customers' comments about the chatbots published in a customer complaint website while shopping from an e-commerce site or app. First, 89 customers' complaints were imported from a customer complaint platform to a single document. Then, the document was subjected to content analysis using a qualitative research tool, Maxqda Plus 2022, and each comment was categorized under related complaint categories. Second, the frequency of customer complaints categories was calculated using the same tool. Additionally, visual maps for each category were created to make the complaints more understandable. While these categorical variables have been addressed in previous studies, variables based on consumer feedback have only been included in this study. According to the research findings, the most frequent customer complaint category is about meaningfulness (with a share of 47.6% in the general total). The least frequent ones are the inability to find a real contact person and the absence of chatbot service (with a share of 7.9%).

**Keywords:** E-commerce, Chatbot, Customer experience, Customer satisfaction, Dissatisfaction

## 1. Introduction

The service provided by companies through consumer support lines plays a leading role in customer satisfaction. The content and speed of consumer response is related to corporate performance (Jayachandran et al., 2004). The faster the response to a request or complaint or the solution offered, the quicker consumer dissatisfaction is eliminated (Harrison-Walker, 2001). A live support service that provides assistance at any time creates high costs and effort since it is carried out by customer support staff. It also requires a technical infrastructure that needs to be integrated into a website, mobile site, or mobile application and requires instant data flow. Therefore, taking steps such as extending the first call resolution process and creating a pre-reception team with less technical knowledge stand out as cost-reducing measures (Davenport & Klahr, 1998). The software called "Chatbot" was first developed in 1994 at MIT under the name of Eliza (Arya, 2019). These programs answered customer questions at a very low cost by providing automatic answers according to various keywords entered by the user (Othlinghaus-Wulhorst & Hoppe, 2020). These customer conversation applications created an opportunity to communicate with potential and existing customers through different interfaces and had the feature of self-development as the communication experience increased with technologies such as artificial intelligence and machine learning (T.R. Ministry of Commerce, 2020). Companies minimized the cost of staff and maintained a communication channel that could maintain contact with the consumer 24/7 instead of live support (Cui et al., 2017).

Chatbot applications are widely used in e-commerce sites, especially in service-oriented industries such as telecommunications, healthcare, travel, education, and finance (Waghmare, 2019). By the end of 2030, the global chatbot market is expected to reach a total size of USD 3.41 billion (Acumen Research and Consulting, 2022). However, these applications, use pre-prepared answers or comments to answer questions posed by users or customers (Huang et al., 2007), which sometimes do not provide clear solutions and cause a negative experience for users who want to solve their problems with a live person (Davidow, 2003). Companies can provide good customer support via chatbots only if this system is set up correctly. As a result, forty percent of consumers ask for an interlocutor to convey their positive/negative experience rather than the purpose of obtaining information or asking questions (Xu et al., 2017).

This study aims to determine complaint categories about chatbot software by coding the complaints of customers who shop from e-commerce sites. It also aims to determine the frequency level of complaint categories. Trying to solve an issue directly affecting

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customer satisfaction and loyalty with basic software can bring significant risks. Most studies conducted to date have measured the efficiency of chatbot software in terms of technical capabilities and service quality. Rare studies focused on increasing chatbot efficiency by categorizing complaints about a single product/service or situation (Anantaram & Sangroya, 2017; Duan et al., 2021). However, the literature lacks studies that directly analyze active customer complaints and feedback about the chatbot service. This paper is expected to bridge this gap in the literature.

The remaining parts of the study consist of four sections. The second section shares a literature review summarizing the studies on chatbot software. The methodology, which reveals the basic approach adopted by this research, is discussed in the following section. The findings of the study are provided in the fourth section. Lastly, the results and suggestions are presented in the fifth section.

## 2. Literature Review

Past research has focused on both the benefits of chatbot software in terms of cost reduction and fast communication with the customer and the damages caused to companies due to the inability to provide service by a real person. In this context, chatbots were examined concerning their ability to produce meaningful results (Federici et al., 2020), what extent these tools have a human-like sensitivity (Almansor et al., 2021), and increasing the significance level of the given answers (Narendra & Setyaningsih, 2021; Sangroya et al., 2018; Orellana et al., 2021).

Many variables (complaint categories) have come to the fore in previous studies. These variables are meaningfulness, inadequate/incomplete response, presence of a real addressee, usefulness/functionality, quality of service, rationality, and technical competence. Researchers examined the usefulness of chatbots perceived by consumers having chatbot experience and how much these tools can help them in the development context (Brandtzaeg & Følstad, 2017; Jenkins et al., 2007). Another research that applied artificial intelligence, learning process, and role-playing methods (Othlinghaous-Wulhorst & Hoppe (2020) suggested that chatbots are insufficient to understand some customers, especially for specific problems and for issues that require experience or competence and to provide them with a realistic interview experience of the kind they are accustomed to conventional call centers. Similar studies have highlighted that chatbots may provide inadequate and generic responses to specific complaints that require expertise. Therefore, they revealed that such answers could result in customer dissatisfaction (Shawar & Atwell, 2007). Some studies proposed chatbots as an auxiliary element to support real customer representatives (Temple & Elie, 2019). In addition, past studies also suggested that chatbots may have difficulties in using the language of the country served with a stable fluency and distinguishing the truth and falsity of the messages conveyed, while it is effective in understanding complaints, problems, and errors and in reporting appropriate answers (Liu et al., 2022).

In studies involving different variables other than meaningfulness, researchers discussed (Crolic et al., 2022; Chung et al., 2020; Collins et al., 2022; Kuberkar & Singhal, 2020) the anthropomorphic view attributed by the consumer to the chatbots offered instead of the live customer representative. These studies revealed that since there is no real interlocutor, customers frequently perceive the respondent as a chatbot, and they tend to be dissatisfied, especially after a negative shopping experience. When users think the interlocutor is human, not a chatbot, they often share positive social media messages about the service they receive, and complaints decrease (Cheng & Pan, 2021). In some cases, although chatbots provide correct and meaningful responses to the fundamental questions related to the subject of the service, they may be insufficient in solving complex problems (Othlinghaus-Wulhorst & Hoppe, 2020; Khan & Rabbani, 2020). Although Chaves and Gerosa (2020) used different variables such as proactivity, communicability, meeting user expectations, responding appropriately, not deviating from the topic, being able to communicate like a human being, and efficient negotiation in their research on an interactive chatbot design, they gathered all variables under the heading of intelligence in the context of meaningfulness and rationality as a function. Suhaili et al. (2021), who made a systematic evaluation of chatbot software produced with different technologies, stated that the common point of the studies on this technology is the variables related to human similarity (existence of a real interlocutor) and the precision of the given answer (insufficient/incomplete response).

Unlike the studies that concluded that the meaningfulness variable was not efficient enough, in a study conducted during the pandemic period when people did not communicate physically with each other, five different scales of recommendation scores were revealed based on consumer feedback. This study found that chatbots exceeded expectations by an 8.6 satisfaction score (Dosovitsky & Bunge, 2021). Similarly, it was stated that a chatbot prepared to provide career planning support service on Facebook, the world's largest social media platform, satisfied the users by finding and transmitting the requested information. It was also stated that a chatbot can diagnose previously defined diseases of patients after talking to them online (Rigamonti et al., 2021). However, it is believed that chatbots still have difficulties in responding to more comprehensive and personalized complex complaints with meaningful messages, except for the usage of predefined keywords and contents (Ni et al., 2017). In fact, for a chatbot that can produce helpful and accurate responses, the purpose of use and the subject of support need to be determined very specifically (Gashi et al., 2021; Narynov et al., 2021). Raundale and Sawale (2021) revealed that the accuracy of the responses

may exceed 90% when the scope is narrowed. Van Den Broeck et al. (2019) believes that the messages given by chatbots that can produce meaningful answers can be used efficiently, even for advertising purposes (Van Den Broeck et al., 2019).

As users who experience the chatbot system and believe that the interlocutor is a real representative, they perceive it as providing a quality and reliable service. Other studies revealed that customers would be more satisfied regarding service quality when the chatbot system ability to react like a real person (the presence of a real interlocutor) was increased. In contrast, customers may turn to be skeptical of the advice and answers they receive when they know that there is computer software in front of them (Zamora, 2017; Narasiman et al., 2019; Bührke et al., 2021; Hill et al., 2015; Følstad et al., 2018). Another study highlighted the result that the response time of the chatbot is prolonged in users with slow connections, related to internet speed, which is another criterion used in terms of technical competence in the evaluation of chatbots (Suresh et al., 2021).

Various markets need to respond to consumers instantly. On the other hand, since it requires more technical competence, follow-up, and service effort, it is known that there is no live support or alternative chatbots on the websites of businesses or e-commerce pages operating as a marketplace. Although it has certain flaws or does not provide the expected level of service, the existence of chatbots reveals the support effort supplied by an organization to contact the consumer and solve possible problems. In this context, the absence of chatbot service should be evaluated as a complaint category. Table 1 shows which variables have been examined in past studies by comparing the current paper's variables.

**Table 1.** Past Studies and Used Variables in These Studies

| **PAST STUDIES** | | Crolic et al. (2022); Chung et al. (2020); Collins et al. (2022); Kuberkar & Singhal (2020); Cheng & Pan, (2021); Zamora, (2017); Narasiman et al. (2019); Bührke et al. (2021); Følstad, et al. (2018) | Temple & Elie (2019); Othlinghaous-Wulhorst & Hoppe (2020); Gashi et al. (2021); Van Den Broeck et al. (2019); Narynov et al. (2021); Raundale & Sawale (2021); Liu et al. (2022); Sangroya et al. (2018); Chaves & Gerosa (2020); Federici et al. (2020); Almansor et al. (2021); Behere, et al. (2020); Rigamonti, et al. (2021); Orellana et al. (2021) | Suresh et al. (2021); Temple & Ellie (2019); Shawar & Atwell (2007); Anantaram & Sangroya (2017); Lin et al. (2017); Suhaili,et al. 2021) | Brandtzaeg et al. (2017); Jenkins et al. (2007); Othlinghaus-Wulhorst & Hoppe (2020); Khan & Rabbani, (2020); Dosovitsky & Bunge (2021); Duan et al. (2021) |
|---|---|---|---|---|---|
| **Variables included in the current study** | | **Common Variables in the past studies** | | | |
| **Meaningfulness** | | **X** | ✓ | **X** | **X** |
| | **Automatic Responses** | **X** | **X** | **X** | **X** |
| | **Receiving Responses in a Limited Category** | **X** | **X** | **X** | **X** |
| | **Insufficient/incomplete response** | **X** | **X** | ✓ | **X** |
| | **Irrelevance of the responses to the Question** | **X** | **X** | **X** | **X** |
| | **No Response** | **X** | **X** | **X** | **X** |
| **Lack of a real interlocutor** | | ✓ | **X** | **X** | **X** |
| **Usefulness** | | **X** | **X** | **X** | ✓ |
| | **Quality of Service** | ✓ | **X** | **X** | **X** |
| | **Rationality** | **X** | ✓ | **X** | **X** |
| | **Primitiveness/Level of advancement** | **X** | **X** | **X** | **X** |
| **Technical Competence** | | **X** | **X** | ✓ | **X** |
| **Absence of Chatbot Service** | | **X** | **X** | **X** | **X** |

## 3. Method

Complaint sites where a negative experience with a brand's product or service is shared are often the first public channels consumers think of to provide feedback (Harrison-Walker, 2001). For this reason, Turkey's most known and visited independent customer complaint platform was used to identify complaints about chatbot services of different e-commerce companies. Each complaint was examined in detail, and irrelevant complaints were eliminated. Then, 89 customers' complaints were collected in a single document.

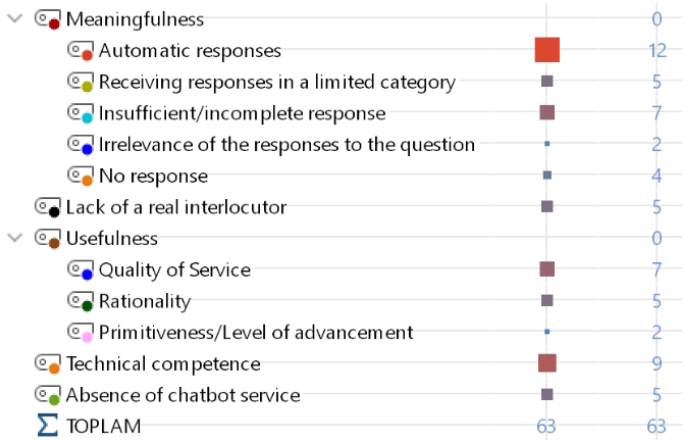
The document, including all complaints, was subjected to content analysis and coded in the Maxqda program to obtain complaint categories. Then, visual maps were created using obtained codes and related complaints through Single case model analysis and Code-subcode segments model analysis in the Maxqda program (Release 22.0.0).

## 4. Findings

### 4.1. Frequency Analysis of Complaint Categories

In this study, the complaint categories were first obtained by coding the complaint texts. Then, the frequency level of the complaint categories was determined by selecting the documents column from the "Code Matrix Browser" in the "Visual Tools" menu in the Maxqda program. The frequency values of the complaint categories are shown in Fig. 1. The large or small shapes represented by the square in the figure show the intensity of the customers' complaints in the relevant category. The intensity of the customers' complaints in the relevant category can be understood also by the total number in the same line as the relevant category.

**Figure 1.** Code Matrix Browser Showing Frequency of Complaint Categories



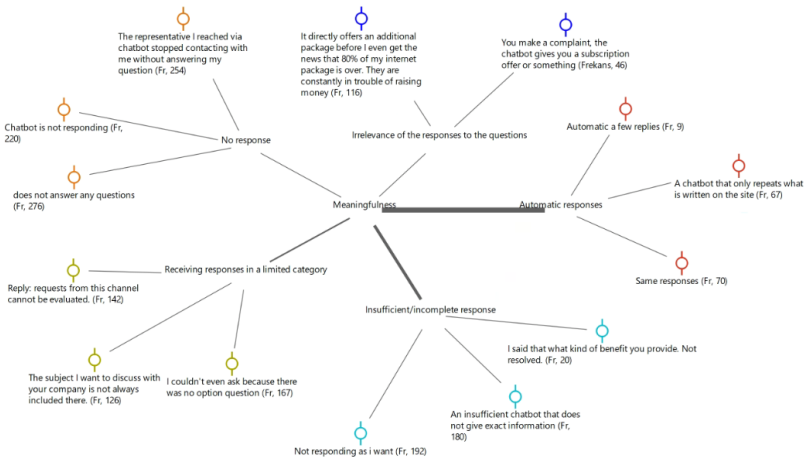

According to the analysis results in Fig. 1, meaningfulness comes first as the main category of customer complaints, with a share of 47.6% in the general total. Accordingly, the most common and obvious problems created by using chatbots are issues such as irrelevant responses, incomplete or insufficient information given in a narrow scope, or not receiving a complete response. However, the main categories in which consumer complaints were gathered the least are the inability to find a real interlocutor, with a share of 7.9% in the general total, and the absence of chatbot service.

The automatic responses come first in the sub-categories, with a 19% share in the general total. Customers believe that chatbots are far from finding solutions to specific problems due to the accepted answers, and they give the impression that a service is offered to the consumers, albeit perfunctorily. The findings show that the sub-category with the least frequency, a share of 3.1% in the general total, is primitiveness/level of advancement.

### 4.2. Visual Maps for Customer Comments under Each Category

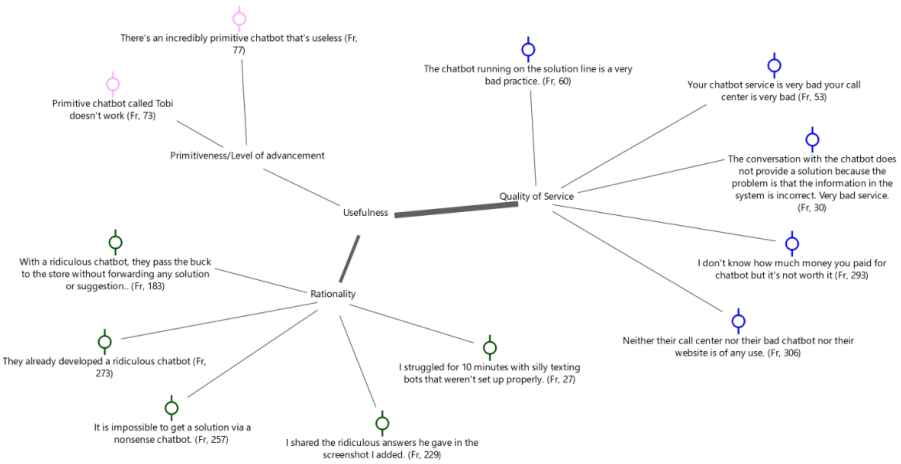
In the last stage of the research, visual maps were created to clearly show customer complaints and interpret them under each complaint category. These maps for complaint categories with sub-codes were obtained via code-subcode segments model analysis, while the ones without sub-codes were created by Single-Case Model (Coded Sections) analysis in the Maxqda. The complaints under each category and where the complaints are mentioned in the text are shown between Fig. 2 and Fig. 6.

**Figure 2.** Code-Subcode Segments Model Analysis for Meaningfulness Category



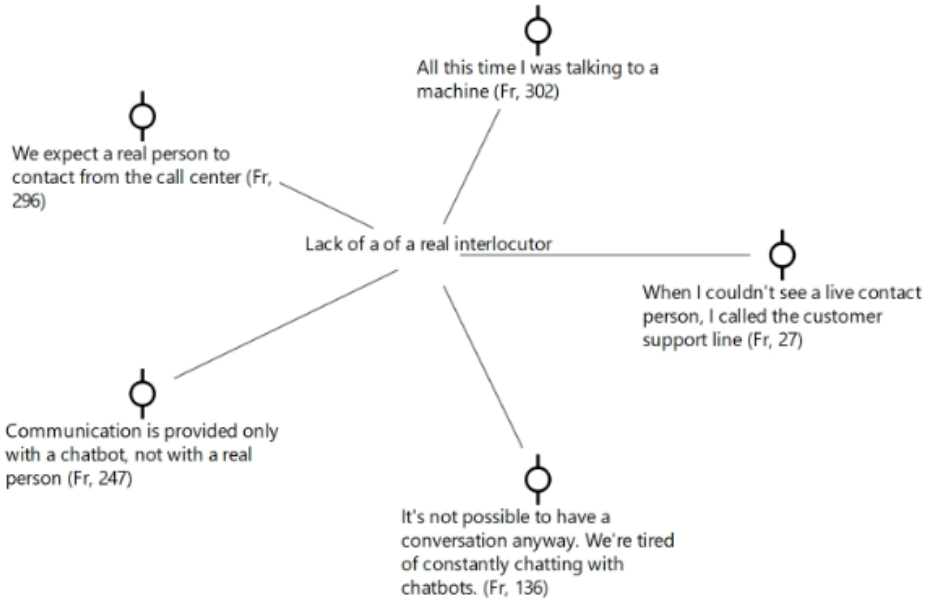
As seen in Fig. 2, there are five sub-categories under the meaningfulness category. The common feature of these sub-categories is that they represent the problems that customers experience in getting answers. Customers often complain because of receiving no, limited, incomplete, monotonous, or irrelevant responses. For instance, customers can find the responses irrelevant when they already have a problem that needs to be resolved but receive offers that may cause additional financial liability through chatbots. The communication realized in such situations can be turned into a negative customer experience.

**Figure 3.** Code-Subcode Segments Model Analysis for Usefulness Category




As shown in Fig. 3, there are three sub-categories under the main category of usefulness. The common feature of these sub-categories is that they consist of expressions in which customers explain their negative experiences with intense emotions. When the contents of the feedback are examined, it is seen that the customers use the support service, even if it is in the form of a chatbot, with the expectation of performing a specific function. For this reason, a call that seems unproductive regarding functionality or usefulness creates high dissatisfaction factors, especially in service quality.

**Figure 4.** Single Case Model Analysis for Lack of a Real Interlocutor Category




As seen in Fig. 4, the Lack of a Real Interlocutor category includes five statements. The common feature of these expressions is that they reflect a point of view that the customers find the service provided by the chatbot inadequate compared to a real interlocutor.

**Figure 5.** Single Case Model Analysis for Technical Competence Category

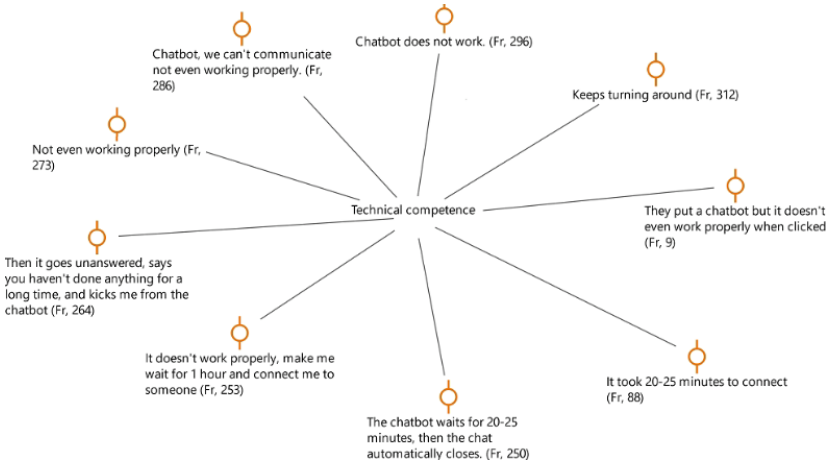
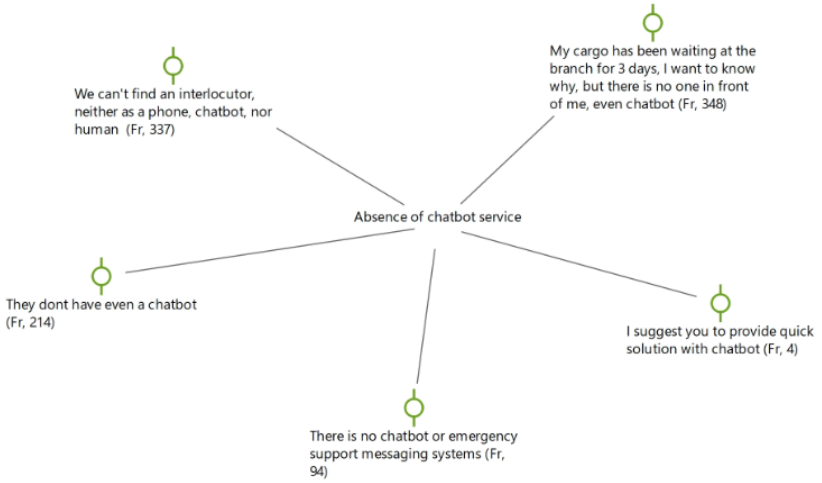



Fig. 5 shows the complaints under the Technical Competence category. These complaints focus on not functioning correctly and systematically.

**Figure 6.** Single Case Model Analysis for Technical Competence Category




Customers also claim the lack of chatbot service as a subject of complaint. The complaints under the Absence of Chatbot Service category are presented in Fig. 6.

## 5. Conclusion

This research focuses on determining the complaint categories concerning chatbot service based on the feedback of the users who shop from e-commerce sites and come with the expectation of conveying various questions, requests, and demands by using chatbot software. From this point of view, all the data in the research have been analyzed in line with the different variables that have emerged in the studies of the chatbot system so far and have been analyzed to reflect the expectations and evaluations of Turkish users. When the results of the research are evaluated, it is observed that consumer groups in various markets covering various products or services, regardless of the industry, want to communicate quickly and practically, whether they want to receive information or support about a problem or experience they have, or request feedback. In line with this expectation, companies that do not have the opportunity to provide live support services due to financial or operational limitations should offer at least a convenient channel to their consumers through a chatbot application.

It is a positive factor that consumers find contact with them, even if it is a chatbot. However, planning the chatbot service to cover the content of information and help requests is critical to success. In fact, according to the research findings, the main topic that consumers complained about the most was the lack of meaningful feedback. For this reason, companies or institutions that do not have the opportunity to provide live support but want to meet a particular consumer demand by using chatbots do so only if they

are competent to create sufficient content coverage; otherwise, this well-intentioned approach, which wants to create satisfaction even with limited resources, will cause serious customer dissatisfaction. This research's finding that meaningfulness-related issues have created the highest level of dissatisfaction confirms this fact. Therefore, it would be better not to offer a chatbot service instead of an inefficient chatbot service in terms of user experience.

Users expect to find a live contact person as the standard to have a good customer experience and find satisfactory solutions to their problems. Since conventional customer relations are realized in this way, when individuals recognize that the system they are messaging, despite its live support appearance, is chatbot software that shares pre-prepared answers, they may have more prejudice against this system. For this reason, companies first need to give a prompt or message to their users on the chatbot interface that will make them feel that this system is an automatic message platform. In addition, chatbot service should be considered a tool for a preliminary assessment that will enable users to categorize their problems and direct them to the right solution point (using it as a front desk) instead of solving all specific consumer needs.

Today, artificial intelligence (A.I.) applications, which are very successful in terms of semantic competence, are gradually developing and becoming widespread. These applications, like ChatGPT, expand their content diversity by improving themselves in line with user responses. In the near future, it is highly probable that these applications will meet the needs of companies in a broader perspective through machine learning and become the leading software in the background with applications such as chatbots that aim to provide 24/7 consumer support. For this reason, it is beneficial for industries that require instant consumer communication to create chatbot systems with the proper planning. However, instead of planning it as a stand-alone customer support service, it would be appropriate to consider it as an auxiliary resource that can optimize the load of limited human resources before live support.

The research has limitations. This study used only data from the most widely used complaint site in Turkiye. Therefore, this research lacks data from other complaint sites and resources. In addition, this research focused on only Turkish e-commerce companies. In this respect, conducting the study in different markets is vital to obtain more generalized results.

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