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Exploring the potential use of generative AI for learner support in ODL at scale

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Highlights

- Explores the potential use of GenAI for learner support in massive open and distance learning environments.
- Investigates how different GenAI-based chatbots can respond to administrative questions that a rule-based chatbot cannot answer and how these chatbots can be better utilised as virtual assistants in ODL.
- Demonstrates the potential of GenAI to provide learners with continuous, more natural, and personalised support.
- GenAI-based chatbots are able to recognize questions written by learners at a higher level than rule-based chatbots.
- GenAI-based chatbots that can work together with rule-based chatbots (hybrid model) are more successful in understanding learner questions and generating answers.

Article Info: Research Article

Keywords: *Generative artificial intelligence, ChatGPT, chatbot, learner support services, open and distance learning*

Abstract

This study addresses the applicability of generative artificial intelligence (GenAI) within the administrative learner support services at Anadolu University Open Education System, a giga university with more than one million learners in Türkiye. The study reveals the performance differences between a rule-based chatbot and different GenAI-based chatbots using a qualitative case study approach. Learner inquiries that the rule-based chatbot could not answer, and frequently asked questions (FAQs) were posed to ChatGPT and Bing Copilot applications in four different cases. The 708 answers in these scenarios were evaluated by three experts. It was observed that GenAI matched learner questions more effectively than the rule-based chatbot. Additionally, Bing Copilot was more successful in generating responses to learners' questions from the internet compared to ChatGPT, which utilized the FAQ dataset. The study reveals that Gen-AI based chatbots that can work together with rule-based chatbots are more successful in generating answers. Findings demonstrate the potential of GenAI to provide learners with continuous, more natural, and personalized support. These findings offer significant insights into how administrative support services in mass-scale educational institutions can be transformed.

1. Introduction

Interest in open and distance learning (ODL) is continually increasing due to its time and location independence, as well as its flexible structure (Gunawardena & McIsaac, 2004). Simonson et al. (2012) define ODL as an institution-based, formal education in which learners, instructors, and learning resources are separate in terms of time and place, and interaction occurs through information and communication technologies. However, in this mode of education, learners may face difficulties in communicating, accessing learning resources, and receiving assistance. Accordingly, learner support services play an important role for the success of ODL institutions (Mills, 2003). The importance of learner support has been frequently emphasized in various studies (Keegan, 1996; Moore & Kearsley, 2012). Support services can be offered to prospective learners, registered learners, and graduates in various forms, including

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administrative, technical, academic, and pedagogical (Keast, 1997; Rekkedal & Qvist-Eriksen, 2003; Rowntree, 1992; Simpson, 2012; Tait, 2000; Thorpe, 2003).

With the proliferation of ODL institutions, the ensuing interinstitutional competitive environment has made it imperative to provide effective support services that meet learners' needs and expectations (Lentell, 2003; Rumble, 2000). Adequate support services to many learners are possible with well-organized institutional-level support services (Sanchez-Elvira et al., 2018). Particularly in giga universities with a learner population exceeding one million, there is a need for innovative support services to meet learners' expectations. The emergence of chatbots have enabled to provide more effective, interactive and personalized support services in ODL at scale (Tonbuloğlu, 2023). Moreover, the advancement of generative artificial intelligence (GenAI) technologies has significantly improved the quality of chatbots. However, there is a lack of studies that investigate the potential use of GenAI as a learner support tool in ODL, especially for a massive number of learners.

2. Literature

2.1. Background and Conceptual Framework

When examining the history of ODL systems, initial support for learners was provided face-to-face, via telephone, or through printed materials; subsequently, radio and television were incorporated into support services, and the development of information and communication technologies initiated the use of tools such as short messaging, email, and websites (Rahm & Reed, 1997). With the advancement of artificial intelligence-based applications, ODL institutions have shifted toward services offering "human-machine" interaction instead of traditional "human-human" interaction by means of using chatbots. Research has also been conducted on models that could utilize GenAI in customer support, similar to learner support (Reinhard et al., 2024). Nowadays, AI applications are widely used across various sectors, including health, communication, digital marketing, banking, psychology, and education (Abdelkader, 2023; Agharia et al., 2024; Al-Fatlawi et al., 2024; Chung et al., 2020; de-Lima-Santos & Ceron, 2022; Dempere et al., 2023; Fan et al., 2023; Liu et al., 2024; Malik & Zaheer, 2024). In addition to the development of AI applications, the advancement of LLM and NLP has significantly improved the service quality of chatbots.

Chatbots are computer programs developed using specific algorithms to execute instructions based on set conditions (Pulist, 2022). They also can mimic human-like interaction patterns using NLP structures (Shumanov & Johnson, 2021). Rooted in the 1950s, chatbots have passed the Turing test and have evolved with advancements in AI; chatbot applications continue to develop today (Ait-Mlouk & Jiang, 2020). ELIZA, a chatbot developed in 1966 by Joseph Weizenbaum in a therapist role, is recognised as the first historical chatbot (Han & Lee, 2022). Studies classify chatbots based on different criteria; notably, rule-based (keyword-dependent) and generative (contextual) chatbots stand out in terms of their operational logic (Arun et al., 2019; Gupta et al., 2020; Suta et al., 2020). Rule-based chatbots are developed by expert teams using FAQs and answers (Akia & Fraboni, 2023; Choque-Díaz et al., 2018; Rocio & Wesley, 2020). With the development of LLM and NLP, GenAI-based chatbots have reached a high capacity for information processing and response (Geckin et al., 2023). Introduced by OpenAI in 2018, the GPT language model aims to emulate language understanding and generation capabilities (Cascella et al., 2023). In other words, the model can understand the context from a text sample and logically generate new texts. The widely acclaimed GPT-3.5 LLM, released by OpenAI in November 2022, along with chatbots like Copilot (formerly Bing Chat), Vard, and Ernie (Han & Lee, 2022; Kim et al., 2022; Rudolph et al., 2023), have become valuable tools in ODL by engaging in real-time interaction with learners and answering their questions (Lappalainen & Narayanan, 2023; Naidu & Sevnarayan, 2023; Rasul et al., 2023). Earlier utilized chatbots in education have gained significantly enhanced support potential following these developments. Integrating these technologies into learner support services across various dimensions, such as websites, mobile applications, social media platforms, and phone channels, carries significant potential for providing more comprehensive support. How this integration will be managed administratively is among the important research topics (Akter, et al. 2023).

A question-answer database prepared by humans can be considered organic, whereas responses generated by GenAI applications are termed synthetic (Bozkurt, 2023a). Notably, as applications like ChatGPT and Copilot are generative, their responses can be described as synthetic. NLP systems like ChatGPT are notable for their ability to interact with users and present synthetically produced responses from the resources provided. This model, capable of serving large audiences without problems of scale, can generate significant synthetic data depending on user interaction. GenAI can automatically recreate or update its responses based on changes in the sources. Firat and Kuleli (2024) compared ChatGPT and Google search engine and concluded that ChatGPT provides superiority in providing personalized information compared to traditional search engines. Although these responses can be produced in a high-quality manner, making them difficult to distinguish from responses given by real humans, there is also a possibility of hallucinations within the responses.

In educational institutions, especially within the scope of administrative support, chatbots that can match answers with a previously human-prepared database, though limited in comprehension capacity, can provide more accurate responses as they rely on official and correct information. In applications such as instant response chatbots, it is only possible for institution officials to check the synthetic information at a later time. Therefore, developing new models with high accuracy rates, whether organic or synthetic, is crucial (Sadhotra et al., 2023). In the development of these models, every accurate and effective dialogue between chatbots and learners has the potential to be used as a source for the production of synthetic data. While rule-based or GenAI systems have advantages and limitations, selecting the organic and synthetic data to be used in developing these systems is crucial.

2.2. Theory of Independent Study and the Role of AI-Based Chatbots

Theory of Independent Study was defined by Charles Wedemeyer (1975) as a learning-teaching activity in which teachers and learners perform their duties and responsibilities separately and communicate in different ways. This theory aims to provide learners with independence and flexibility at all stages of the learning process. Wedemeyer (1975) states that an effective distance learning environment should be based on four basic elements: the teacher, the learner, the learning system and the content to be learned. These elements should be organized in such a way as to substitute the learning space and provide sufficient choice and autonomy for the learner.

In this context, technological tools and especially AI-based chatbots play an important role in the implementation of independent study theory. The rule-based chatbot used in Anadolu University Open Education System provides flexibility and speed to the learners by responding immediately to their administrative questions. These systems facilitate learners' access to information in accordance with their learning speed, time and preferences. In particular, AI-based chatbots offer a time and space independent learning environment to support the individual learning experience. In addition, they allow learners to manage their own processes by providing instant feedback. Such tools have the potential to strengthen individual learning processes in open and distance learning environments as effective tools that support independent study theory.

2.3. Research Objectives

This study aims to investigate how different GenAI-supported systems can respond to administrative questions that a rule-based chatbot cannot answer and how these systems can be better utilized as virtual assistants in ODL. For this purpose, four different cases have been developed. The first two cases utilize strategies that match ChatGPT with organic responses. In comparison, the other two cases examine the accuracy of the synthetic responses produced by ChatGPT and Bing Copilot. The research questions representing each case are as follows:

1. When only FAQs are given to ChatGPT, how effectively can the GPT-3.5 version match the FAQs with learners' questions that the rule-based Anadolu University Open Education System (AU-OES) chatbot cannot answer?

2. When both FAQs and their answers are given to ChatGPT, how effectively can the GPT-3.5 version match the FAQs with learners' questions that the rule-based AU-OES chatbot cannot answer?
3. When FAQs and their answers are given to ChatGPT, how effectively can the GPT-3.5 version generate responses to learners' questions that the rule-based AU-OES chatbot cannot answer?
4. How effectively can the Bing Copilot application (without sharing data related to FAQs) generate responses to learners' questions that the rule-based AU-OES chatbot cannot answer?

2.4. Research Environment: Anadolu University Open Education System (AU-OES) and Learner Support System

Anadolu University is a dual-mode public open university in Türkiye with 1.8 million learners and more than four million graduates in its Open Education System (since 1982). The university provides 63 undergraduate and associate-level distance learning programs in Türkiye and 41 countries worldwide and it has 100 contact offices in Türkiye and abroad.

Learner support systems play a critical role in the organization of the AU-OES as they provide accessible and flexible learning opportunities at scale. In the context of academic support, synchronous online sessions are provided for over 500 courses per semester. Social support is provided via radio programs, official social media accounts, and Online Learner Communities. Administrative support is provided via offices, SMS, social media, Call Center Service, FAQs, Question Tracking System, and the chatbot on the website (Erdoğdu & Gümüş, 2023; Öncü, 2024).

2.5. AU-OES Chatbot

The AI-supported chatbot at AU-OES can be classified among closed chatbots that use rule-based, structured data sources and are directed only toward a specific area. It aims to provide accurate answers by trying to match the questions typed by users with FAQs previously given to them. If this match is above 35%, it provides the relevant answer; if it is below, it requests the question again. Institutional officials are responsible for the matching of questions that the chatbot could not match. Therefore, to enhance the performance of the rule-based chatbot application, relevant experts continuously monitor and update the system.

2.6. Implementation of the Rule-Based Chatbot at the AU-OES

At the start of the project, a team of specialists in the Learner Affairs Department spent three months defining FAQs and answers based on the aosdestek.anadolu.edu.tr address (FAQ set). To better match incoming questions from learners with the FAQ set by the system, each question was written in five different ways, the database was developed, and the model's success was enhanced. The application began serving on the aosdestek.anadolu.edu.tr address with its beta version on November 11, 2022 (Figure 1).

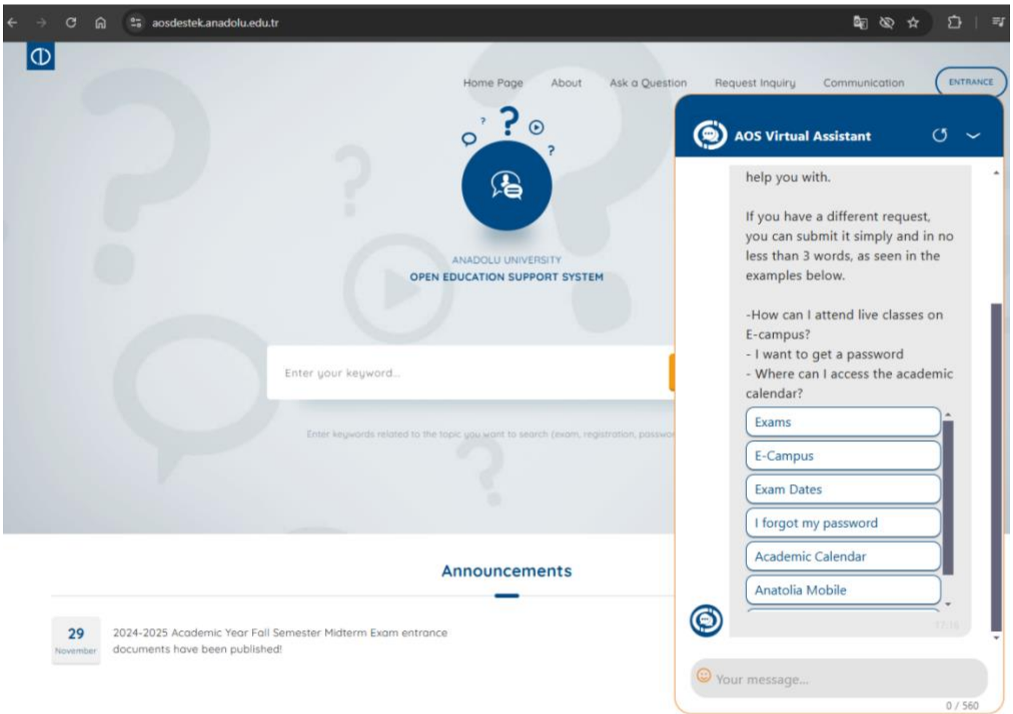

Fig. 1. Interface of the Chatbot Serving at aosdestek.anadolu.edu.tr

During the first eight months of its single-interface usage (November 11, 2022–June 11, 2023), the chatbot had 100,255 users. During this period, 104,108 dialogues and 1,192,773 messages were generated. Starting from March 2023, dialogues that the chatbot requested three times but could not match, are redirected to office staff during weekday working hours. The operation of the system is depicted in Figure 2.

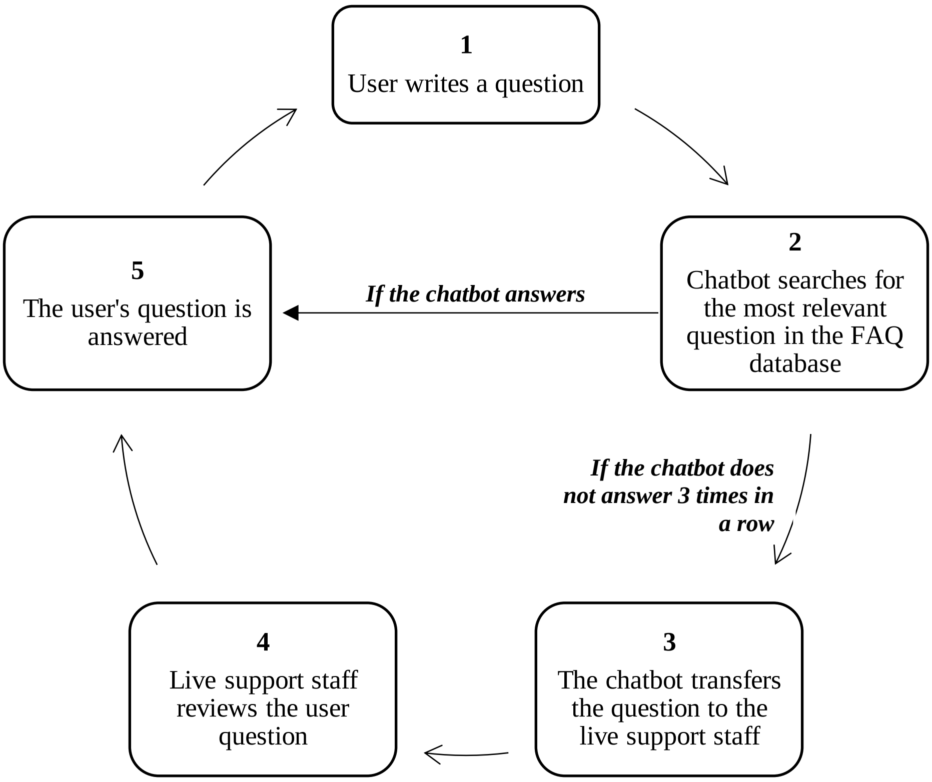

Fig. 2. The Workflow of the Chatbot

AU-OES institutional officials carefully compile the chatbot's FAQ database to ensure that the questions and answers are distinct. Additionally, questions that the chatbot cannot match (below 35%) can be answered after a feedback process. After each operation, the chatbot application is trained (Figure 3).

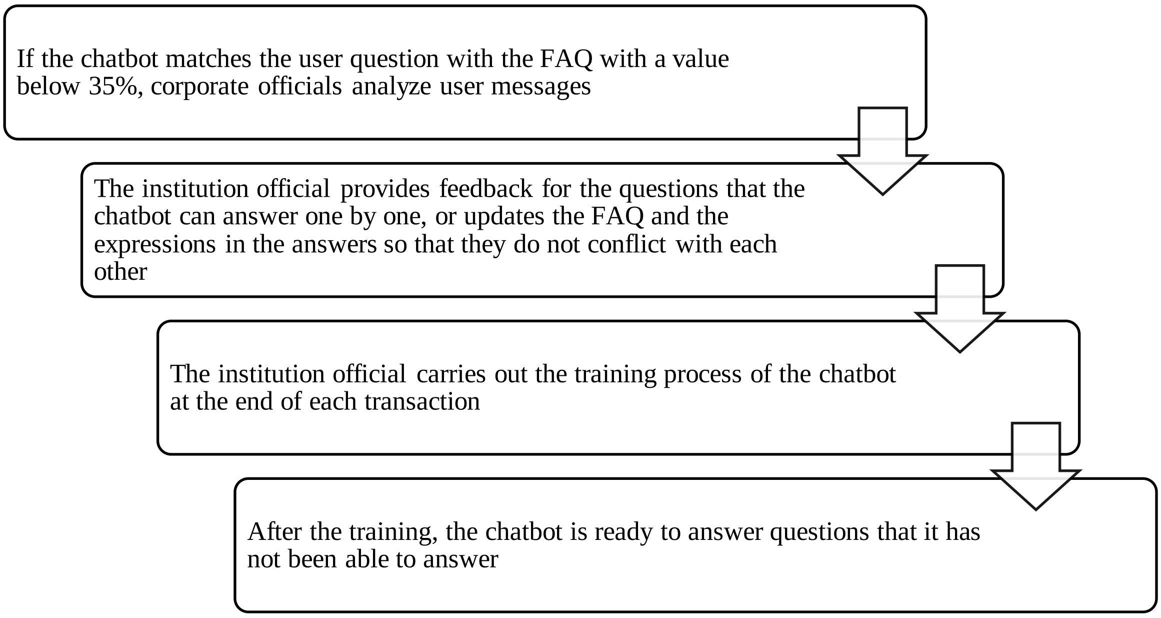

Fig. 3. The Stages of Operations Conducted by Institutional Officials in the Chatbot

The application filters the keywords in the questions written by the learner and compares them with all the questions in the FAQ list to find the closest match and respond to the learner. Therefore, the words in the questions within the chatbot's FAQ database must not overlap as much as possible. In this system, users using different words despite having the same meaning can negatively affect the response situation. For successful matching, users are expected to use meaningful and clear expressions in a single message.

Figure 4 illustrates the number of FAQs that the chatbot was unable to answer and was able to answer from November 11, 2022, to June 11, 2023. During this period, the response rate of the chatbot application to user questions recognized as FAQs was 49%, while the non-response rate was 51%. It is noted in Figure 3 that when the registration renewal period ended, the use of this system by learners significantly decreased, as with other support systems.

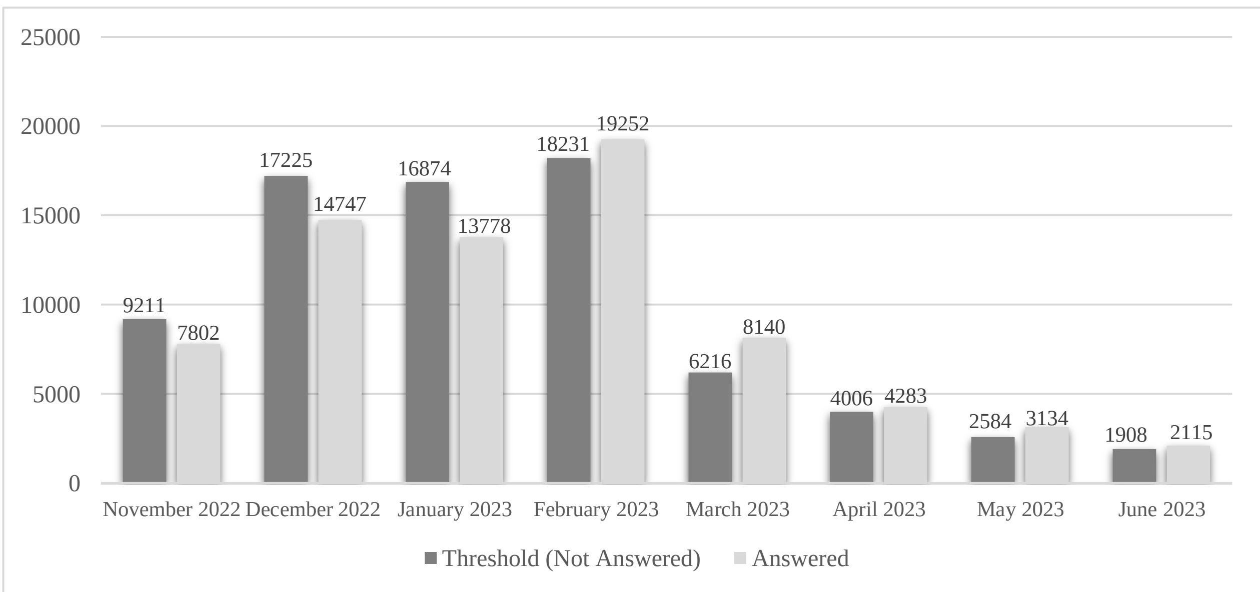

Fig. 4. Chatbot Application FAQ Response Numbers

Figure 4 illustrates the number of FAQ questions that the chatbot was able to answer and was unable to answer from November 11, 2022, to June 11, 2023. During this period, the response rate of the chatbot to user questions recognized as FAQ questions was 49%, while the non-response rate was 51%. It is noted in Figure 3 that when the registration renewal period ended, the use of this system by learners significantly decreased, as with other support systems.

On the other hand, the AU-OES chatbot has some limitations as it is rule-based. Therefore, this study intricately examines how different GenAI-supported systems can respond to questions that a rule-based chatbot cannot answer and how these systems can be better utilized as virtual assistants in ODL.

3. Methodology

3.1. Research Design

The questions and answers used in the study were analyzed by document analysis method. In the document analysis process, the questions that the AU-OES rule-based virtual assistant could not answer within the scope of learner support services were systematically analyzed in a document and then compared with the answers given by both GenAI applications. In this study, descriptive statistics were utilized along with the document analysis approach. The responses of the GenAI applications were evaluated in terms of frequencies and percentages. The case study design is appropriate for research that involves a deep examination based on data from any given event, individual, or process (Creswell & Poth, 2024). In this study, in addition to the rule-based chatbot used by AU-OES, two different GenAI - ChatGPT and Bing Copilot - have been included in four different scenarios. The study used a holistic multiple-case study design, as it involves multiple cases, each considered holistically and compared within its context (Yin, 2018).

ChatGPT is a chatbot developed by OpenAI that is available after membership. Bing Copilot is also an AI tool developed by Microsoft with GPT-4 integration and does not require membership. The reason for the preference of these two AI tools is their popularity and their competence in the field of higher education (Rudolph et al., 2023). Additionally, both tools are easily accessible and free of charge.

The researchers played coordinating and supervisory roles in the data collection and analysis processes. In particular, they established and ensured the implementation of standardized protocols for testing GenAI applications and evaluating responses. Their areas of expertise include AI-enabled educational technologies, digital publishing, open educational resources, instructional design, and student support services.

3.2. Data Collection Tools and Data Analysis Procedures

Data were obtained through content analysis of responses provided by the relevant GenAI application in each case. The study used 177 questions that learners asked the rule-based AU-OES chatbot between November 11, 2022, and June 11, 2023, which were unanswered, contained more than 20 characters, and had a minimum of five repetitions. Four cases were developed to evaluate the performance of different GenAI applications. Three staff members with at least 10 years of experience in Anadolu University Open Education System and specialized in distance education, educational technologies or student support services were involved in the process of evaluating the answers used in the research. The experts were selected based on their knowledge of artificial intelligence applications in learning environments and their previous experience in similar projects. Subject matter experts analyzed the responses generated at the end of each case to determine their success rates. Table 1 shows the procedures in each case sequentially.

Table 1.

Cases

Strategy No.	App.	Has AI Been Given FAQs?	Has AI Been Given FAQ Answers?	Prompt Summary	Explanation of the Answer
1	ChatGPT (GPT-3.5)	Yes	No	The AI was asked to match learners' questions with the most suitable FAQ provided	The AI matched learners' questions with the most suitable FAQ provided
2	ChatGPT (GPT-3.5)	Yes	Yes	The AI was asked to match learners' questions with the most suitable FAQ and answers provided	The AI matched learners' questions with the most suitable FAQ provided
3	ChatGPT (GPT-3.5)	Yes	Yes	The AI was asked to answer learners' questions based on the FAQ and answers provided	The AI generated responses to learners' questions using the most suitable FAQ provided
4	Copilot	No	No	The AI was asked to answer learners' questions	The AI generated responses to learners' questions

3.3. Validity and Reliability

Within the research, 708 transactions were conducted using GenAI-supported applications. The responses generated were checked and analyzed by three experts at AU-OES. Since Copilot is an application with a search engine feature developed integrally with Bing, questions were directly posed to it. According to Miles and Huberman (1994), the agreement percentage was found to be 0.96. So, there was minimal disagreement among the experts in the evaluation of 25 transactions.

3.4. Limitations

The research was based on the FAQ question set prepared by AU-OES for the rule-based chatbot, as well as the questions asked by learners to the rule-based chatbot on the specified dates. Furthermore, the results of the study were based on the characteristics, structure, and capacity of ChatGPT and Copilot at the time of the research.

4. Findings

The research findings are presented below according to the cases developed within the scope of the research objectives.

RQ1. *Findings on the ability of ChatGPT to match FAQs with learners' questions that the rule-based chatbot could not answer when such FAQs are provided to ChatGPT*

After providing the FAQs to ChatGPT (GPT-3.5 version) beforehand, it was observed that ChatGPT matched the questions posed by learners to the rule-based chatbot with an FAQ question at a rate of 72.32%. The findings related to the first research question are shown in Table 2.

Table 2.

Findings for Case 1

Case No.	Total	True	False	%
Case 1	177	128	49	72.32

Examples from Case 1 are listed in Appendix-1.

RQ2. *Findings on the ability of ChatGPT to match FAQs with learners' questions that the rule-based chatbot could not answer when both FAQs and their answers are provided to ChatGPT*

When ChatGPT is provided with an FAQ question and its answer beforehand and asked to match the questions written by learners in the rule-based chatbot to an FAQ question, the AI accurately matches learners' questions with FAQ questions at a rate of 95.48%. The findings related to the second research question are shown in Table 3.

Table 3.

Findings for Case 2

Case No.	Total	True	False	%
Case 2	177	169	8	95.48

Examples from Case 2 are listed in Appendix-2.

RQ3. *Findings on the ability of ChatGPT to generate responses to learners' questions that the rule-based chatbot could not answer when FAQs with answers are provided to ChatGPT*

When ChatGPT is given an FAQ question and answer beforehand and asked to respond to questions written by learners in the rule-based chatbot, the AI can correctly answer learners' questions 54.24% of the time. The findings related to the third research question are shown in Table 4.

Table 4.

Findings for Case 3

Case No.	Total	True	False	%
Case 3	177	96	81	54.24

Examples from Case 3 are listed in Appendix-3.

RQ4. *Findings on the ability of Bing Copilot to correctly generate responses to learners' questions that the rule-based chatbot could not answer without sharing data related to FAQs*

Two separate evaluations were conducted in this last case. Initially, when the Bing-powered ChatGPT (GPT-4 version)-supported Copilot application was asked to answer FAQs based on information on the internet without sharing any data, the AI was able to provide correct answers at a rate of 42.77%. However, when Copilot was similarly asked to respond to questions that the rule-based chatbot could not answer, it could provide correct answers at a rate of 64.97%. This indicates that Copilot is better at answering learner questions than the FAQs written by institutional experts. The findings related to the fourth research question are shown in Table 5.

Table 5.

Findings for Case 4

Case No.	Total	True	False	%
Case 4	177	115	62	64.97

Examples from Case 4 are listed in Appendix-4.

The responses given by different GenAI applications according to the designated case have been evaluated together with experts from the Open Education Support System. The FAQs listed in the ChatGPT (GPT-3.5 version) and Bing Copilot applications and the questions that learners could not have a response in the rule-based chatbot were considered. The evaluations have led to an analysis of the distribution of correct and incorrect answers by AI, detailed in Table 6.

Table 6.

Number of Correct and Incorrect Answers for GenAI Applications According to All Cases

Case No.	Total	True	False	%
Case 1	177	128	49	72.32
Case 2	177	169	8	95.48
Case 3	177	96	81	54.24
Case 4	177	115	62	64.97

As Table 6 shows, the performance of GenAI varies depending on the platform and case. The most successful operation for GenAI was under the second case on the ChatGPT (GPT-3.5) platform, where it matched questions with provided FAQ questions and answers (95.48%). The least successful scenario occurred when ChatGPT (GPT-3.5) was asked to respond to learners' questions, even though FAQs and answers were provided (Case 3, 54.24%). On the other hand, the Bing Copilot application, which used the internet as a source for answering questions, was observed to generate more successful responses (64.97%). Additionally, using user questions as a source rather than FAQs has shown that synthetically generated responses could be a more successful resource.

Overall, the cases devised in the research indicate that GenAI support services are more successful in matching existing question sets but less successful in generating answers. However, it is important to note that these results depend on the FAQ sets used in the research context and the environments utilized by AI systems to answer questions.

5. Discussion and Conclusion

Higher education institutions use various systems for learner support services. Particularly in distance education, systems that can effectively and efficiently utilize current technologies stand out. An example is the AI-supported chatbot used for administrative support in AU-OES.

In the research, it was observed that the rule-based AU-OES chatbot had a 49% success rate in the matching of learners' questions. Although this success rate might seem low, the risk of incorrect answers is very low because it provides the relevant answer directly once the question is understood. The research showed that ChatGPT, which has higher NLP capabilities, was much more successful in matching unanswered questions by AU-OES chatbot. Particularly in the second scenario, where FAQs and answers were provided, it was observed that 169 out of 177 unanswered questions were correctly matched (Table 3). Despite such high matching success, the success was considerably lower (54%) when direct answers were requested from ChatGPT in the third scenario. The Bing Copilot application, on the other hand, was able to generate more successful answers by utilizing information from the internet (65%). However, since these sources could not be limited, synthetic answers generated from incorrect or outdated sources were observed. It is anticipated that clarifying the internet sources used by Copilot could increase this rate. For example, the MyGPT application allows users to create AI-powered chatbots while being able to select sources on the internet. However, the tools and features used in the research show that GenAI technologies are not yet sufficiently capable of generating responses for learner support applications. Also, in Strategy 4, when FAQs were directly asked to Copilot, the success rate of answering (42.77%) was lower than the success rate of answering the direct expressions written by learners (64.97%). The results show that it is more difficult for Copilot to answer FAQs written in a formal writing style, but questions written in the learners' language are answered more successfully. This situation can be associated with the advanced NLP capacities of AI models. A better understanding of learners' writing language could allow synthetically generated data to be used as a resource when necessary.

It is crucial for chatbots to understand questions as accurately as possible and to provide appropriate responses based on the data set. Approaches such as utilizing more sources and machine learning might be more suitable for enhancing the success of general-purpose chatbots (Ait-Mlouk & Jiang, 2020). However, chatbots, which are expected to provide support based on accurate and up-to-date information in a specific area, are expected to deliver support services with precision. Large-scale institutions' support channels may have generated a large amount of data over time between learners and support staff. However, using this data in the development of chatbots carries some risks. The answers given may vary depending on the learners' situations, the date the question was asked, and the policies applied by the institution. The answers given to learners coming from different registration types or having different GPA scores can vary. For these reasons, it is important to establish models that can direct the conversation to expert staff until the response accuracy of chatbots is improved. In the case of AU-OES, if users' questions are not understood, they are redirected to the next available expert, during weekday working hours. This approach, which can be named a "hybrid support model" allows support personnel to intervene only when the chatbot fails to respond, enabling quick solutions for learners and identifying situations where the support model is insufficient (Sadhotra & Gupta, 2023). In scenarios in which GenAI can directly produce responses or enrich produced responses in learner support services, the authorized staff can see their mistakes and improve themselves. In the model presented by Reinhard et al. (2024), the communication between the customer and the AI is monitored and enriched by the relevant personnel when necessary. This approach not only ensures that the established model increasingly provides more accurate answers but also allows the relevant personnel to analyze the content, thereby creating a more efficient process (Brynjolfsson et al., 2023; Qudah & Muradkhanli, 2024).

One of the fundamental characteristics that determine the communication quality of chatbots is "contextual understanding". Just as meaning can change based on a word, sentence, or block of messages, the ability to interpret new messages throughout the communication process can enable chatbots to deliver more successful results. As an alternative to traditional chatbots, Panda and Kaur (2023) investigated the use of ChatGPT in library and information systems and have concluded that user experience and service quality have improved. Lappalainen and Narayanan (2023) also state that ChatGPT can provide very realistic and human-like answers, continue the conversation by asking follow-up questions, and respond in different languages based on English source data. Thus, GenAI-based support systems can understand the context of a text sample and logically continue with new texts in the relevant context. The lack of contextual understanding in rule-based systems is one of the major disadvantages. Anadolu University's rule-based chatbot does not perceive consecutive messages as a whole, and is limited to previously given answer patterns because it can only use FAQs.

Chatbots are expected to serve a large number of users in different situations within learner support services. Therefore, being able to provide the correct answer according to the learner's status is important. Although AI-supported applications generally give successful results, more time is needed to demonstrate similar success in personalized responses (Akiba & Fraboni, 2023). How well chatbots recognize the user and their ability to utilize the user data are crucial for the improvement of chatbots for personalized support. Systems with access to necessary data through the learner information system and learning management system increase the chance of providing personalized responses to the user, necessitating the development of methods to ensure the protection of personal data in these models (Kalla & Kuraku, 2023). Similarly, for providing correct information regarding registration, payment, and department selection to prospective learners of different graduation levels or with disabilities, it is important to be able to utilize personal data.

The way chatbots present their answers can also make a difference in service quality. The writing style, tone, response speed, and active-passive role of chatbots vary according to their area of use in the literature. Mukherjee, Hudeček, and Dušek (2023) have shown that a polite writing style synthetically generated from everyday speech language performs better for chatbots. Research by Chaves et al. (2019) on different chatbot models that can be used as tourism assistants also emphasized that a more interactive writing language can create a more polite tone for users. It has been observed that chatbots used in the customer support channel provide higher levels of social presence when they use informal language (Liebrecht et al., 2021). Chaves and Gerosa (2021), who reviewed 56 studies in different fields, researched how social characteristics can affect human-chatbot interaction and predicted that certain features could support establishing natural interactions. Chocarro, Cortinas, and Marcos-Matas (2023), who examined teachers' attitudes toward chatbots in education, argued that a formal writing style is more effective than the use of emojis and social language. Even the dimension of emotional intelligence has been suggested as an important variable in chatbots providing effective and customizable support (Bozkurt, 2023b; Prinz, 2022). Educational institutions can determine the style of chatbots according to the type of support they provide and the characteristics of their target audience, and they can offer certain options to be chosen by the users. Even adapting to the users' writing style to offer a more personalized approach can further increase participation (Shumanov & Johnson, 2021).

Mass-service educational institutions provide support services to users with very different characteristics. The acceptance of text-based communication environments by these users has long been recognized (Yang & Jolly, 2008). With the widespread use of chat services, research has been conducted on which types of users prefer this communication environment or find it more functional. In one of the first studies on the classification of chat service users (Rajaobelina, Brun & Ricard, 2019), data was collected from 682 users and it was observed that 13.8% of the participants, aged 18-24, used the chat service an average of 4.34 times in the last year. The second group consisted of users aged 25 years and older with tablets and mobile phones and in good financial condition (average of 2.65 in the last year). The third group, which constituted 30% of the participants and stated that they used the chat service with a computer, remained below the average (2.05 times a year on average). The group that used chat services the least was found to be computer users aged 35-44 years or 55 years and older (Rajaobelina, Brun & Ricard, 2019). In a similar study, potential users of chat services were investigated. In a two-stage clustering analysis on 342 users, the intensity of interest was specified in 4 groups (Rajaobelina & Ricard, 2021). It was found that women were more interested in the relevant services than men, users in the 35-44 age range were after these two groups, and the least interested users were the elderly (Rajaobelina & Ricard, 2021). When these studies are analyzed, it is seen that it is important that virtual assistants connected to productive artificial intelligence technologies are given the option to communicate in accordance with the users' own preferences. Educational institutions can offer students of different ages and characteristics the option to customize the writing style and visual features of the virtual assistant instead of a formal language based on legislation. Thus, users can customize according to their own wishes instead of a single standard decided by the institution.

Providing individually accessible support is an important quality in mass-service educational institutions. However, providing continuous individual support in a human-dependent manner in institutions with high number of learners requires a costly and complex structure. FAQ pages, social media platforms, video channels, offices, call centers, and email or ticket-based correspondence systems are particularly aimed at meeting administrative and technical support needs. However, individual support services dependent on human resources could be insufficient during important processes in the academic calendar, exam periods, and especially crisis times like COVID-19. Although Anadolu University has nearly 100 offices across all 81 cities of Türkiye and about 500 expert staff who worked through a special infrastructure to provide online support during the pandemic, call response rates dropped to about 10% during this period (Erdoğdu, 2022). AI-supported chatbots, although they require special integration, a compact question-answer database, infrastructure, and staff, once configured, can operate 24/7 and provide service independently of user scale. Moreover, the need for a high number of personnel who are continuously equipped with up-to-date information will also be eliminated. Allowing learners to receive quality answers whenever they want can reduce the feeling of isolation and prevent loss of motivation (Oliveira et al., 2019). In a study investigating the use of AI-powered chatbot (in student support services at an institution providing higher education services), the researchers found that communication through the chatbot was faster and more effective than other types of communication (Nurshatayeva et al., 2020). It is also important that chatbots are used more creatively in the field of academic support, rather than being seen as a standard support platform. In this way, students' motivation and achievement can be increased. In the Lifelong Learning Centre (LLC) at the University of Leeds, UK, a chatbot named "Bo" was introduced as a pilot study in the 2020-2021 academic year (Abbas et. al., 2022). The platform aimed to create a community between students and mentors beyond a standard chatbot, and it was stated that especially the engagement of different student groups and international students could be increased with this tool. After 3 weeks of use, a survey sent out emphasized that students were generally positive about the environment (Abbas et. al., 2022).

Some users treated the AU-OES chatbot as a real person and tried to ask questions or complain. Araujo (2018) in his study on the identity and appearance of chatbots suggested that the use of human-like language or names could help the chatbot be perceived as human. However, it is considered more important to present systems that provide "virtual" support in this way in terms of transparency, trust, ethics, and user experience. Also, no matter how advanced AI-supported systems may be, they have not yet reached the level of dialogue that can be established with a real person. Considering the identity of chatbot (whether seen as robots or humans), their psychological impact and the possibilities of hallucination in support services are important (Rad & Rad, 2023; Skjuve et al. 2019).

6. Recommendations

It is important to note that AI-powered chatbots must be fed with suitable information sources to generate accurate data. Limiting AI to official websites, FAQs, and institutional regulations can help produce correct synthetic answers. Outdated content, guidelines or old pages can mislead chatbots that use these pages. Thus, keeping the content up-to-date is essential.

Enhancements could be made to improve the capacity of chatbots to understand user questions. Rule-based systems typically use a matching model in which each sentence or message is evaluated separately. However, this approach needs to consider the contextual nature of user data. To overcome this, flowcharts could be developed that holistically evaluate messages written by users with a model high in NLP capacity. Additionally, informing learners about the service and providing brief training on how to phrase their questions could enhance efficient use (Hmound et al., 2024). Prompt engineering is essential in AI usage, as user skills in interacting with AI-powered chatbots can improve efficiency (Bozkurt, 2023b).

Developing a chatbot for an educational institution requires a unique infrastructure and dedicated time. However, once chatbots reach a certain level, they can be made available to users through multiple channels. Chatbots supporting chat areas via application programming interface (API) integration on other web pages can be linked with mobile apps. This helps text-oriented users get help when and where they need it. Additionally, chatbots can be integrated into the chat sections of the institution's social media platforms. Besides real-time support, chatbots can provide asynchronous responses in the institution's official communication systems (email or ticket-based systems) and offer voice support in call centers using speech-to-text and text-to-speech approaches. Providing learners with 24/7 synchronous or asynchronous support can positively impact learning, retention, and success (Dempere et al., 2023; Hmound et al., 2024). Chatbots can also be used institutionally for staff in geographically dispersed or large-staffed institutions, reducing in-service training costs and enhancing corporate presence and coordination (Arun et al., 2019).

Support services should be able to be tailored to different types of users and learner statuses when needed. Integrating the information from the learner information system with sensitive handling of personal data can significantly improve the quality of service. Especially in an academic context, personalized feedback can make learning processes more effective (Chang et al., 2023). In ODL, disengagement or dropout is a significant issue (Tait, 2014). Promptly identifying learners who might drop out and providing the proper support is necessary (Paniagua & Simpson, 2018; Simpson, 2012). Chatbots providing reactive or proactive support based on learner information and learning management systems data can enhance support services. Administrative and academic support can be more qualitative and individual; pedagogically, learners can receive more practical guidance. Thus, chatbots can proactively provide special alerts, reminders, and feedback for learners when necessary.

Educational institutions may need help to choose between rule-based and GenAI systems. Chatbots that have a high rate of correct answers but relatively low understanding can be supported by hybrid models. The highest success rate in this research was observed when ChatGPT was asked to match the answers to questions that the rule-based AU-OES chatbot could not answer (95%). While all learners' direct use of ChatGPT services may increase cost and complicate integration, referring to ChatGPT when rule-based systems fail to recognize questions might be more efficient. In scenarios where rule-based or GenAI-supported models are insufficient, referrals can be made to third-level subject matter experts. This model can initially accommodate learners with limited human resources or during crises, providing simultaneous and asynchronous support with fewer staff.

Both human-operated and AI-supported support models are susceptible to providing incorrect or false information. Continual monitoring of the system can allow for the identification and improvement of errors or weaknesses in the model. In this context, user feedback will be the most crucial data for development. Rating user satisfaction after each interaction and additionally collecting open-ended feedback are highly significant for system improvement. This enables tracking of how user satisfaction is distributed across different topics or questions. Furthermore, open-ended feedback allows for clearer collection of user opinions. This method can also differentiate whether user satisfaction is with the service or the response. In some cases, even if learners' requests are correctly addressed, the dissatisfaction it creates for them can lead to perceived low service quality. Therefore, using qualitative data along with quantitative data can more clearly reveal the actual state of the model.

Monitoring correspondence between GenAI systems and users is crucial, especially to identify responses that are approved or liked by users. According to two findings from the last case used in the research, it was observed that direct answers to user questions were more successful than responses based on the institutionally written FAQ set in formal language. Institutions can use the synthetic answers generated from each successful dialogue between the chatbot and users as a data source in subsequent phases.

When chatbots operate based on GenAI technologies, users can be given the chance to choose writing styles that suit their age and preferences. Mass-service distance education institutions can provide options to personalize the writing style and visual features of the chatbot for learners of various ages and characteristics. This allows users to customize according to their preferences, rather than being restricted to a single standard set by the institution.

It is anticipated that economically viable models for the mass-scale use of GenAI systems in educational institutions will develop over time (Lappalainen & Narayanan, 2023). In this scenario, institutions can more easily integrate or develop their own AI systems. IBM's Watson, for instance, can be used extensively as a chatbot system and has been researched for use as a chatbot in educational settings (Goel & Polepeddi, 2016; Oliveira et al., 2019; Rocio & Wesley, 2020). Systems like OpenAI's MyGPT, on the other hand, save institutions from the cost of developing NLP and LLMs, allowing them to work with ready-made libraries, templates, and prompts (https://chat.openai.com/gpts/mine). Different GenAI models can also be set up to operate on institutional servers (on premises) rather than connecting to general cloud-supported services.

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Appendices

Appendix 1. Examples from Case 1

Correct Examples

- Learner's Question (LQ): "I want to change my exam entry location."

- Artificial Intelligence Matching (AIM): "I want to change my exam center."

Incorrect Examples

- LQ: "As learners of Anadolu University Open Education Faculty, our exemption application for English, Turkish Language, and Revolution History courses made during the initial registration was not accepted for various reasons…"

- AIM: "No relevant FAQ found."

Appendix 2. Examples from Case 2

Correct Examples

- Learner's Question (LQ): "As learners of Anadolu University Open Education Faculty, our exemption application for English, Turkish Language, and Revolution History courses made during the initial registration was not accepted for various reasons…"

- Artificial Intelligence Matching (AIM): "As learners of Anadolu University Open Education Faculty, we want to apply for an exemption for English, Turkish Language, and Revolution History courses made during the initial registration."

Incorrect Examples

- LQ: "e-campus is giving an error."

- AIM: "How can I register as a new learner?"

Appendix 3. Examples from Case 3

Correct Examples

- Learner's Question (LQ): "I want to register."

- Artificial Intelligence Answer (AIA): "For detailed information about registration procedures, you should follow the official announcements of the Open Education Faculty…"

Incorrect Examples

- LQ: "I can't access the courses."

- AIA: "Registration is usually done through the learner automation system. You can find the option to register in the relevant menu and follow the necessary steps."

Appendix 4. Examples from Case 4

Correct Examples

- Learner's Question (LQ): "Where is my food order?"

- Artificial Intelligence Answer (AIA): "Your food order question is unrelated to the Open Education System. Please get in touch with the food company from which you ordered."

Incorrect Examples

- LQ: "How can I get my learner card?"

- AIA: "You can obtain your learner card from your Open Education office after registration…"