

BichoBot – A Chatbot to Assist in the Reception of Incoming University Students

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Abstract. *The beginning of the journey in a higher education course is often surrounded by doubts from incoming students about various topics such as scholarship policies, course characteristics, library use, university restaurant, among other aspects of university life. Information about these topics is often found on different websites and documents, which makes it difficult for incoming students to find. Given this difficulty, actions that centralize this information to help students identify it become necessary. Thus, in this context, this article presents BichoBot, a chatbot developed to support freshmen in accessing institutional information at the Federal University of Ceará (UFC) - Quixadá Campus. BichoBot involves the use of the Rasa and RAG frameworks, with a LLaMA 3 language model. BichoBot offers contextualized and reliable answers via Telegram. The proposed solution was evaluated by UFC freshmen, demonstrating good performance in addressing the most common questions from students.*

1. Introduction

University freshmen often face challenges adapting, especially when accessing institutional information that is usually dispersed across multiple documents and websites. This decentralization makes it difficult for new students to find and absorb essential content.

At Federal University of Ceara (UFC) campus in Quixadá (UFC-Quixadá), important information to freshmen students is spread across various domains, including General Statutes¹, student assistance services, and library guidelines². Actions to support freshmen like PET-Recebe [Sampaio et al. 2024] have identified the need for centralized and interactive access to such institutional information during student orientation.

On the other hand, Artificial Intelligence (AI) has transformed how we interact with technology, making virtual assistants and chatbots essential tools for obtaining quick and accurate information, as demonstrated in recent applications that integrate language models with conversational frameworks [Rocho et al. 2024]. Currently, these systems not only facilitate interaction between users and technology but have also become a fundamental requirement in the search for information quickly and efficiently. A chatbot is an automated dialogue agent that processes natural language inputs and provides relevant information in response. This system has limited interpretive competence, often restricted to a particular area of knowledge [Rahman et al. 2017].

¹<https://www.ufc.br/a-universidade/documentos-oficiais/326-regimento-geral-da-ufc>

²<https://biblioteca.ufc.br/pt/>

Therefore, this work presents BichoBot, a chatbot developed to assist freshmen with campus and institutional questions. It uses a layered architecture combining RASA [RASA TECHNOLOGIES 2025], RAG [Lewis et al. 2020], and a Large Language Model (LLM) to provide contextual, human-like responses. This approach enhances handling of ambiguous or informal queries common among new students [Rochó et al. 2024, Kuratomi et al. 2024]. BichoBot was tested with a set of questions and positively evaluated by UFC-Quixadá freshmen, validating its effectiveness.

This paper is organized as follows: Section 2 presents background on freshmen challenges and chatbot development; Section 3 covers related work; Section 4 describes the methodology; Section 5 details BichoBot's features and testing; Section 6 presents the evaluation; and Section 7 concludes and discusses future work.

2. Background

This section describes concepts about Welcoming Freshman Students and challenges; and chatbot development.

2.1. Welcoming Freshman Students

[Andriola and Araújo 2021] found diverse perceptions on course quality and academic support among Federal University of Ceará undergraduates, with many struggling to integrate despite broader access policies.

Similarly, [Teixeira et al. 2008] highlight that freshmen face emotional, academic, and social challenges requiring autonomy and knowledge of institutional processes. Without adequate support, insecurity and demotivation arise, underscoring the need for clear and effective welcoming strategies focused on guidance.

2.2. Chatbot's Development

Chatbot's originated from simple rule-based systems and evolved into more complex ones with the help of Natural Language Processing (NLP) and Natural Language Understanding (NLU), enabling computers to interpret user intentions, emotions, and entities in text [Shawar and Atwell 2007, Sidhu et al. 2013, Ait-Mlouk and Jiang 2020]. Today, with the use of *Large Language Models* (LLMs), such as ChatGPT, chatbot's are able to simulate more realistic and fluid conversations, being widely adopted to automate user interactions [Bender and Koller 2020, Zeng et al. 2023].

A relevant advancement is the *Retrieval-Augmented Generation* (RAG) technique [Lewis et al. 2020], which combines external information retrieval (from databases, documents, or API's) with answer generation. This allows chatbot's to go beyond their internal knowledge, providing more updated and contextualized responses.

Among the available frameworks, RASA [RASA TECHNOLOGIES 2025] stands out as an open-source platform for building chatbots. It is composed of two main components:

1. Rasa NLU: responsible for interpreting user intents and extracting entities;
2. Rasa Core: manages conversation flow using machine learning to predict the next action based on dialogue history.

The main technologies used include:

1. NLP/NLU: for interpreting human language;
2. LLMs: for large-scale natural language generation;
3. RAG: combining retrieval with response generation;
4. Rasa: for chatbot development and orchestration.

3. Related Work

This section presents works that served as theoretical and comparative references for the development of BichoBot, discussing similar solutions implemented in different contexts.

[Machado et al. 2025] introduces SIAC-MICA, a tool designed to support freshmen adaptation at the Federal University of Southern and Southeastern Pará. It integrates a web platform and chatbot, populated with information by course coordinators, and includes a response management panel. BichoBot draws inspiration from this approach but focuses on the specific context of Federal University of Ceará, Quixadá campus, targeting the most frequent information needs of its freshmen.

[Neto et al. 2022] proposes a chatbot to answer frequent student questions related to courses, internships, and academic pathways. Unlike this broader scope, BichoBot concentrates on welcoming freshmen, aiming to centralize key information and use accessible language integrated with commonly used institutional services.

[dos Anjos Afonso 2024] explores the development of academic virtual assistants to reduce the burden on traditional service channels and enhance student autonomy. BichoBot aligns with this vision but is distinguished by its focus on the onboarding process of new students at Federal University of Ceará, Quixadá campus.

4. Methodology

The methodology for this study was developed in four stages. In the first stage, we defined BichoBot's architecture. This involved identifying the conversational interfaces, selecting the structure to be used and determining the databases required. In stage 2 we carried out data analysis and pre-processing. During stage 3, we developed BichoBot. This involved generating the model's training data, implementing personalized actions and configuring integrations, in stage 4, we carried out some tests and finally, stage 5, where we carried out a study with freshmen students from the UFC-Quixada.

5. BichoBot

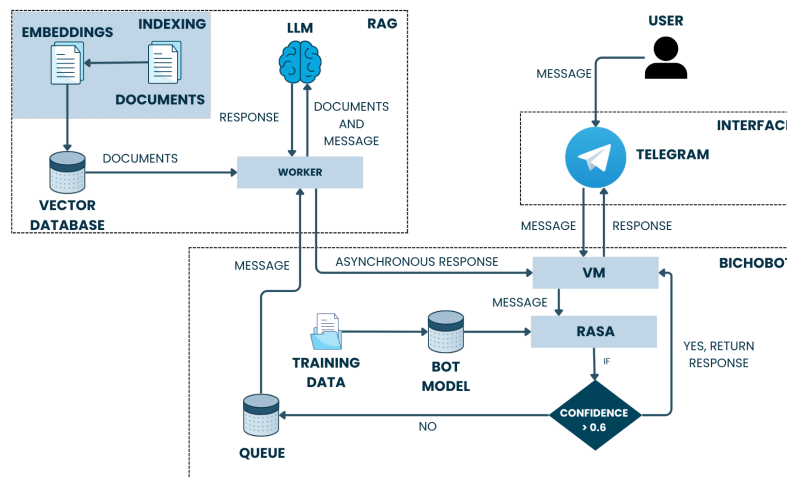
This section describes BichoBot's development stages: architecture (Section 5.1), data collection and preprocessing (Section 5.2), and development details (Section 5.3). The source code is publicly available³.

5.1. Architecture

The Figure 1 presents the proposed architecture for BichoBot.

RASA was responsible for answering frequently asked questions, while RAG (Retrieval Augmented Generation) handled broader inquiries related to more dense documents. RAG determines the most similar "chunks" (segments of text) to a question stored

³<https://github.com/sheiely/bichobot>



in the vector database through similarity calculation, while the LLM (Large Language Model) is responsible for generating the final response context for the user.

We chose Telegram⁴ as the communication platform because it is easily accessible and offers native bot support. Plus, it is a tool widely used by undergraduate students. This way, the responses generated by the services are sent directly to the user's chat. In addition, the campus provided a VM (Virtual Machine) to host BichoBot's services. Users can access the chatbot on Telegram⁵.

The system uses Qdrant⁶ as the vector database to store and retrieve document embeddings relevant to the user’s input. To generate contextualized responses, it leverages a large language model (LLM) executed locally via Ollama⁷. In this setup, the LLM used is LLaMA 3⁸. These components form the backbone of the RAG (Retrieval-Augmented Generation) architecture, enabling the fallback mechanism to combine precise document retrieval with advanced natural language generation. It was also necessary to implement a message queue with Redis⁹ to avoid overloading the server and to ensure that messages would be responded to.

5.2. Data Analysis and Preprocessing

An essential step in building the bot was the analysis and pre-processing of data¹⁰. During this step, we surveyed the main sources of information, including institutional documents, relevant data about the university, important documents such as the General Regulations¹¹, notices, official websites, as well as academic rules and procedures. We also

⁴<https://web.telegram.org/>

⁵https://t.me/ufc_bicho_bot

⁶<https://qdrant.tech/>

⁷<https://ollama.com/>

⁸<https://ai.meta.com/blog/meta-llama-3/>

⁹<https://redis.io/>

¹⁰[https://drive.google.com/drive/folders/172iZouzZR3MxBOYbq-qzmD6R85ooJAFh?](https://drive.google.com/drive/folders/172iZouzZR3MxBOYbq-qzmD6R85ooJAFh?usp=sharing)

¹¹<https://www.ufc.br/a-universidade/documentos-oficiais/326-regimento-geral-da-ufc>

used the Freshmen Survival Manual, which gathers important information about scholarships, available services, and campus life.

5.3. BichoBot Development

BichoBot consists of two integrated services that respond to user requests. This subsection details the RASA implementation in Section 5.3.1 and the RAG implementation in Section 5.3.2.

5.3.1. Rasa implementation

The chatbot was developed by using the Rasa framework, primarily responsible for orchestrating the bot and answering simpler, more static questions. The project was divided into stages, starting with organizing 11 main topics based on frequent freshmen doubts: assistance, library, scholarships, courses, location, bus, projects, Quixadá, university restaurant, systems, and general. These topics were defined based on the Freshman Survival Guide [PET Conexão dos Saberes 2025] and consultations with senior students.

A total of 79 intents were associated and distributed by topic as follows:

Table 1. Distribution of the 79 associated intents by topic

Topic	Number of Intents
Assistance	9
Library	9
Scholarships	3
Courses	9
Location	3
Buses	4
Projects	3
Quixadá	7
University Restaurant	12
Systems	16
General	4
Total	79

A fallback policy was implemented with the `nlu_threshold` parameter set at 0.6, establishing the minimum confidence threshold to classify intents. If confidence was below this threshold, the `action_default_fallback` was triggered, integrating the RAG server and forwarding the user input to a service that searches domain documents and generates contextualized answers via retrieval and generation techniques.

5.3.2. RAG Implementations

For more complex questions beyond Rasa’s basic scope, Retrieval-Augmented Generation (RAG) was used, capable of answering using various file types (HTML, DOC, PDF, etc.). The documents used to train the model were those mentioned in Section 5.2.

RAG generates responses by selecting the most relevant document parts, which were divided into self-contained paragraphs. These paragraphs were converted into numerical vectors through embeddings generated with Hugging Face models using the Sentence-Transformers library [Reimers and Gurevych 2019], and stored in the Qdrant vector database for efficient similarity search. The most relevant paragraphs found by vector proximity are then provided to the LLM to generate precise answers. The communication and queue management are handled by the service called 'WORKER', as illustrated in Figure 1.

5.3.3. LLM Choice

Llama3 [Meta 2024] was selected after a series of tests where the target audience formulated questions and rated the performance of different LLMs — Mistral [AI 2023], DeepSeek-R1 [Gao et al. 2024], and Llama3 — all with 7 and 8 billion parameters, on a scale from 0 to 10. With RAG implemented, it was possible to compare answers to the question “what’s the nutritionist’s contact info?”, shown in Table 2.

Table 2. LLMs’ Answers

LLM	Answer
Mistral	To contact the nutritionist, their Telegram channel is “Shots de Nutrição”(link: t.me/shotsdenutricao). If you have specific questions or need additional help, you can send an email to nutricao@quixada.ufc.br .
LLaMA 3	You can reach the campus nutritionist via email for questions or to sign up for healthy eating groups at nutricao@quixada.ufc.br . Also, you can join the “Shots de Nutrição” channel on Telegram to participate in discussions about healthy eating: t.me/shotsdenutricao .
DeepSeek-R1	Certainly! The nutritionist is in charge of the “Shots de Nutrição” channel. She uses Telegram to share information about healthy eating and can be reached via the channel at t.me/shotsdenutricao or by email at nutricao@quixada.ufc.br . If you need help or have questions, just access the channel or send an email!

As observed, DeepSeek-R1 8B occasionally mixed languages, making it unfeasible for this project. Additionally, a satisfaction test was conducted with five randomly selected freshmen who freely tested the full system with different LLMs and assigned scores from 1 to 5 for each model. The summed scores are shown in Table 3.

6. Comparative analysis with other chatbots

As we did not identify any other chatbots in the literature developed specifically for this purpose, we chose to compare **BichoBot** with the following LLMs: *Copilot* [GitHub and OpenAI 2023], *ChatGPT* [OpenAI 2023], and *Gemini* [DeepMind 2023]. To this end, a list of questions was created based on the common doubts of freshmen at the UFC-Quixada.

Table 3. Scores of LLMs Models Attributed by Five Evaluators

Evaluator	DeepSeek-R1	Mistral	LLaMA3
1	2	4	5
2	1	3	3
3	3	5	5
4	1	2	4
5	2	4	4
Total	9	18	21

6.1. Question Selection

The questions used to evaluate the chatbot were selected after conversations with freshmen, aiming to identify their main doubts. Table 4 presents the identified questions that were submitted to both the bot and the LLMs.

Table 4. Specific questions asked by freshmen

ID	Question
Q1	Do I need to enroll more than once?
Q2	How do I connect to eduroam?
Q3	What is the UFC-Quixadá WhatsApp group?
Q4	Is there any tutorial for completing my enrollment?
Q5	Where can I find tips for choosing this semester's courses?
Q6	Is there student housing?
Q7	If I face difficulties at the university, who should I contact?
Q8	What are the bus schedules?

We defined specific criteria to evaluate chatbot responses, emphasizing clear, accurate, and contextually relevant information tailored to students' local reality. Since many frequent questions involve campus-specific procedures and services, the bot must avoid generic or incorrect answers that could cause confusion, especially about details varying across campuses or recent updates. Our goal is for the bot to address common questions while providing official guidance, valid links, and pertinent local references. The expected answers to the questions in Table 4 are presented following:

- **Answer to Q1:** Clearly explain whether enrollment is required each semester and how the process works.
- **Answer to Q2:** Inform that the Eduroam login is with @ufc.br and the SIGAA password, providing an official tutorial for UFC students.
- **Answer to Q3:** Provide the official link to the UFC-Quixadá freshmen WhatsApp group.
- **Answer to Q4:** Indicate an official tutorial or step-by-step guide to correctly complete the enrollment.
- **Answer to Q5:** Present reliable tips for course selection, preferably with official links, even if no official link exists.
- **Answer to Q6:** Clearly inform that there is no student housing at the UFC-Quixadá campus, avoiding confusion with the Fortaleza campus.

- **Answer to Q7:** List the actual services at the UFC-Quixadá campus that assist students, such as student assistance, coordination, psychology, etc.
- **Answer to Q8:** Provide the official bus schedules for the UFC-Quixadá campus or the official link for consultation, avoiding confusion with other campuses or universities.

6.2. Comparison Results

Table 5 shows the performance results of each chatbot in answering the questions selected in Table 4, indicating whether their responses met the expected criteria with YES, while questions that did not meet the criteria were marked as NO.

Before posing the questions to the LLMs and BichoBot, we provided detailed context that the user is a freshman at the campus. This allows for a more accurate analysis of the bots' ability to provide correct, clear, and relevant information to the target audience.

Table 5. Chatbot performance in answering freshmen's questions

Question	Copilot	ChatGPT	Gemini	BichoBot
Q1	YES	YES	YES	YES
Q2	YES	NO	YES	YES
Q3	NO	NO	NO	YES
Q4	YES	NO	YES	YES
Q5	YES	YES	YES	YES
Q6	NO	YES	NO	YES
Q7	YES	NO	NO	YES
Q8	NO	YES	NO	YES

For Q1, all chatbots answered correctly. For Q2, only ChatGPT failed to provide a correct response. Regarding Q3, only BichoBot answered satisfactorily. For Q4, ChatGPT did not satisfy the question. For Q5, all chatbots responded correctly. In Q6, Copilot and Gemini failed, while ChatGPT and BichoBot succeeded. For Q7, ChatGPT and Gemini failed to provide satisfactory answers, whereas BichoBot and Copilot responded correctly. Finally, in Q8, Copilot and Gemini failed, while ChatGPT and BichoBot answered successfully.

In summary, Copilot correctly answered 5 of 8 questions; ChatGPT and Gemini each answered 4 of 8; and BichoBot answered all questions correctly.

7. BichoBot Evaluation

This section presents the BichoBot's evaluation survey. This study was based on [Kitchenham and Pfleeger 2002] and conducted with students of the UFC-Quixadá campus. Section 7.1 describes the form and data collection, Section 7.2 presents the participants' profile, Section 7.3 details the quantitative analysis and the qualitative data from this study.

7.1. Data Collection

To evaluate BichoBot, a study was conducted with freshmen from undergraduate courses at the UFC-Quixadá campus.

A questionnaire¹² was developed in three stages: the first collected participant profile information; the second consisted of quantitative questions using a Likert scale from 1 to 5 (1 – Strongly disagree, 2 – Partially disagree, 3 – Neutral, 4 – Partially agree, 5 – Strongly agree); and qualitative questions gathered participant feedback. The questions were based on Unified Theory of Acceptance and Use of Technology (UTAUT) [Venkatesh et al. 2003]. The questionnaire was validated through a pilot test with a PhD professor in Computer Science, after which corrections were made based on feedback.

Participants were recruited via two methods: random approaches on campus, where students interacted with BichoBot and completed the questionnaire, and classroom visits in introductory courses for first-semester students, where BichoBot was presented and the evaluation questionnaire distributed. The study occurred between May and June 2025, with 42 participants.

7.2. Participants' Profile

All participants were first-semester students enrolled in Software Engineering, Computer Engineering, and Computer Science. All identified as students of UFC-Quixadá and reported regular use of smartphones and digital platforms.

7.3. Evaluation Results

The quantitative analysis involved 11 questions (Table 6) covering aspects such as ease of use, language clarity, promoted autonomy, and intention for future use.

Table 6. Mapping of quantitative questions (Q1 to Q11)

ID	Question
Q1	I intend to continue using BichoBot.
Q2	BichoBot is relevant for the freshman's academic life.
Q3	BichoBot facilitates access to important information at UFC-Quixadá.
Q4	Using BichoBot makes adapting to university easier.
Q5	I believe BichoBot is useful for UFC-Quixadá freshmen.
Q6	Using BichoBot helps me solve doubts more quickly.
Q7	BichoBot improves my autonomy as a student.
Q8	BichoBot helps find answers that would be difficult to discover alone.
Q9	BichoBot was easy to use.
Q10	The bot's response time was fast enough.
Q11	The language used by the bot was clear and easy to understand.

The responses obtained show a broadly positive reception of BichoBot. Figure 2 presents the distribution of answers for each of the 11 questions, indicating how many times each value on the scale (from 1 to 5) was assigned per question.

There is a low presence of negative responses, with most evaluations concentrated between 4 and 5, especially on questions related to language clarity (Q11), ease of use

¹²<https://forms.gle/Re2AhSnwKfiafUva6>

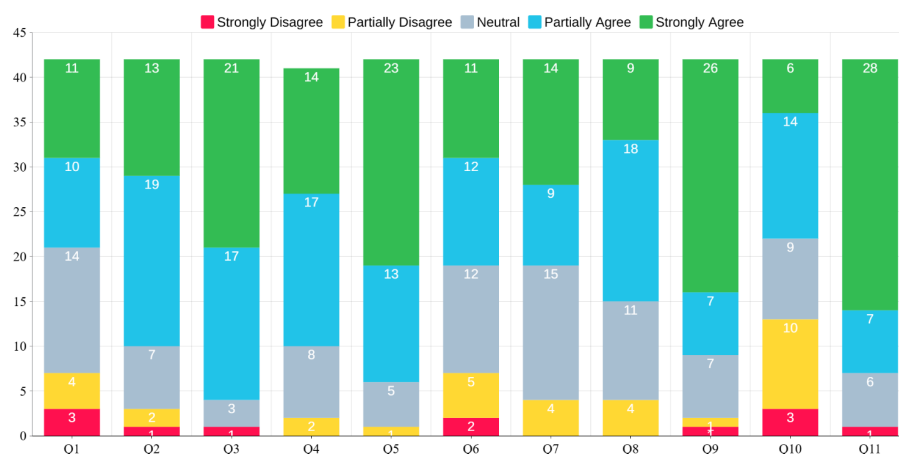


Figure 2. Distribution of responses per question (scale from 1 to 5).

(Q9), improved access to information (Q3), and usefulness (Q5), reflecting the acceptance of the chatbot.

Question Q10, which referred to response time, showed more negative data compared to other questions but still prevailed between neutral and partial agreement. This situation may have occurred due to the limited infrastructure available to host the bot system on campus, which caused delays of a few minutes in responses when many students used the bot simultaneously, a situation reported during classroom tests.

Regarding users' qualitative perceptions, we highlight the need expressed by one participant to access the bot on other platforms. Another identified point concerns the chatbot's slow response time, which was largely due to a lack of technical resources. Another user emphasized the need for a direct menu for the bot's options. It was also suggested to expand the scope of answers to cover more specific topics, such as internships, and to provide a usage tutorial.

8. Conclusions and Future Work

In recent years, chatbot development has advanced significantly, especially in specific domains where technical knowledge and experience are crucial for creating effective solutions. While structured processes exist for developing these systems, there's a growing need for more interactive and dynamic approaches.

In this context, a chatbot named BichoBot was developed to help freshman students at the UFC-Quixadá campus, identify information interactively. The chatbot uses an architecture that combines information retrieval techniques with response generation based on RASA and RAG. For data storage and management, a relational database was used alongside Qdrant, which is responsible for structured domain data. Telegram was chosen as the user interface for interaction.

The chatbot proved suitable for its objective of supporting freshman students in obtaining information about the rules and regulations of the UFC-Quixadá campus, while also improving the user experience in acquiring this relevant information.

As future work, there is a need to evaluate BichoBot's usage by freshman students as their questions arise throughout their first academic term in the university. To this end,

a qualitative study will be conducted in the second academic term of 2025. Additionally, we envision the possibility of generalizing this bot for customized use in any university. This would require creating an administrative module to provide the necessary documents, which would then generate a centralized database with specific information for another university or campus.

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