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Research Paper

Chatbots Implementation for Students Admision

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ABSTRACT: *The growing need for accessible and responsive information services in higher education has highlighted limitations in traditional admission support systems. This study aims to enhance the new student admission process at Universitas Stikubank through the development and implementation of a chatbot based on the RASA framework. The chatbot addresses several key issues: limited availability of staff, the necessity for 24/7 access to information, and the demand for immediate responses to prospective students' queries. By simulating human interactions, the chatbot provides real-time, accurate information about university programs, admission requirements, campus facilities, and more. The development process involved data collection through interviews, observations, and literature review, followed by a structured methodology for conversation modeling and system design. Testing results indicate that the chatbot effectively supports the admission process, reducing administrative workload and enhancing the applicant experience by offering uninterrupted service. This study demonstrates the potential of chatbot technology to streamline administrative processes and improve service quality in the educational sector, particularly in university admissions.*
KEYWORDS: ***Chatbot, New Student Admissions, Higher Education, Natural Language Processing (NLP), Automated Information Service***

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I.INTRODUCTION

In recent years, higher education institutions have faced increased demands to provide more efficient and accessible services to prospective students, particularly during the admission process. The admission phase is a critical time when institutions must respond quickly to inquiries, offering accurate information on topics such as program offerings, application procedures, and campus facilities. However, traditional methods—such as responding to inquiries through email, phone, or in-person meetings—pose limitations in terms of operational hours and staff availability. Many prospective students expect round-the-clock service that meets the pace and convenience of modern digital interactions.

The emergence of chatbot technology presents a promising solution for addressing these challenges in educational settings. Chatbots, defined as software applications designed to simulate human-like conversations through text or voice, have demonstrated their potential in various sectors, including customer service, e-commerce, and healthcare, for their ability to deliver efficient, scalable, and continuous support to users. In educational institutions, chatbots can streamline administrative tasks, providing answers to frequently asked questions, assisting with routine inquiries, and offering real-time guidance, thus alleviating the burden on administrative staff while improving the overall user experience.

This study explores the implementation of a chatbot specifically tailored to support the admission process at Universitas Stikubank (UNISBANK) by leveraging the RASA framework, an open-source platform for developing conversational AI applications. Unlike conventional methods that rely on static question-and-answer formats, the RASA framework allows for the integration of advanced Natural Language Processing (NLP) and machine learning techniques to better understand and respond to user inputs dynamically. Through this research, we aim to demonstrate how a well-designed chatbot can not only increase accessibility and efficiency in the admission process but also enhance the institution's digital presence and appeal to tech-savvy prospective students.

The study is organized as follows: after a review of relevant literature on chatbot applications in education, we discuss the research methodology, including data collection methods and the chatbot development process. We then present the implementation results and evaluate the chatbot's performance in terms of accuracy, responsiveness, and user satisfaction. Finally, we offer conclusions and suggest areas for further research to optimize chatbot technology in the context of higher education admissions.

II.LITERATURE REVIEW

The implementation of chatbots in educational settings has grown significantly in recent years, primarily driven by advancements in Artificial Intelligence (AI) and Natural Language Processing (NLP). Chatbots are defined as software applications capable of simulating human conversations, facilitating automated, efficient, and scalable responses to inquiries. Their application spans diverse fields, from customer service to healthcare, where they have shown potential for reducing administrative workloads and enhancing user satisfaction.

Within the realm of higher education, chatbots have been explored as tools for streamlining administrative processes, especially in student support and admissions. For instance, [1] studied an intelligent chatbot designed to handle student inquiries in Saudi Arabian universities, demonstrating that chatbot technology could effectively manage routine questions, thereby allowing administrative staff to focus on more complex tasks. Another study by [2] implemented a chatbot for educational and vocational guidance in Morocco, showing that chatbots could provide tailored advice and guidance based on students' academic and career interests.

The rise of frameworks such as RASA and Microsoft Bot has facilitated the development of more sophisticated chatbots with capabilities in NLP and machine learning. [3] compared chatbots based on RASA and Microsoft Bot in university settings, noting that RASA offered superior flexibility in managing varied user intents, which is particularly useful for complex inquiries in educational environments. Furthermore, [4] emphasized that AI-driven chatbots have the potential to handle routine customer service inquiries efficiently, with applications in admissions showing promise for similarly enhancing the student experience

NLP is a critical component in chatbot development, enabling systems to interpret and respond to human language. [5] provided an in-depth analysis of how NLP and sentiment analysis are applied in chatbots to improve communication accuracy and relevance. In a study on customer service chatbots, [6] found that NLP allows chatbots to understand user intent and provide accurate responses, which is directly applicable to admissions contexts where students have varied and specific questions.

Research comparing chatbot frameworks underscores the importance of selecting the appropriate platform for specific applications. For example, [7] compared Microsoft Bot and RASA, concluding that Microsoft Bot offered more robust integrations, while RASA excelled in handling complex conversational flows and NLP capabilities. Similarly, [8] found that RASA-based chatbots for educational assistance could deliver prompt responses to students, enhancing their experience when seeking academic support.

Chatbots are increasingly utilized for personalized education, adapting to individual user needs and providing custom responses based on user profiles. [9] explored a conversational recommender system to assist educators in curriculum planning, demonstrating that chatbots can support digital learning by recommending learning outcomes and resources tailored to individual students. In a similar study, [10] developed a chatbot to aid in consultations on health topics for parents of young children, showcasing the broader applicability of chatbot technology beyond traditional educational use cases.

Despite the benefits, chatbot adoption in education faces challenges, particularly regarding the accuracy of responses and user acceptance. For example, [11] highlighted limitations in the adaptability of RASA-based chatbots, noting that responses could be limited if user inputs diverge significantly from the trained dataset. [12] reported similar findings, observing that while chatbots using deep learning models with RNN and LSTM performed well in accuracy and speed, they required continuous training to maintain effectiveness.

Studies by [13] on chatbots for digital customer service and [4] on AI-driven customer interaction highlight the importance of practical, scalable implementations for institutions with high information demands, such as universities during admission periode. [8] emphasize that RASA-based chatbots can enhance student engagement, offering a viable solution for institutions aiming to provide continuous, responsive support.

Moreover, recent developments in NLP and AI are set to further enhance chatbot capabilities. Research by [14] on classification algorithms shows that integrating machine learning techniques, such as K-Nearest Neighbors (KNN) and Naive Bayes, could further improve chatbot response accuracy, an approach that could be beneficial for refining responses in the admissions process.

In conclusion, chatbot technology holds significant promise for higher education, particularly in admissions, where efficiency and responsiveness are critical. The studies reviewed highlight various approaches to chatbot design and the potential of NLP in improving interaction quality. However, challenges remain in areas such as data availability and user adaptation, suggesting a need for further research and refinement to fully realize the potential of chatbots in educational settings.

III.RESEARCH METHODOLOGY

This study adopts a systematic approach to develop and implement a chatbot aimed at enhancing the new student admission process at Universitas Stikubank (UNISBANK). The methodology is divided into two primary stages: data collection and chatbot development. The chosen methodology reflects a combination of qualitative and technical approaches, ensuring that the chatbot is designed to meet the specific needs of prospective students and admission staff.

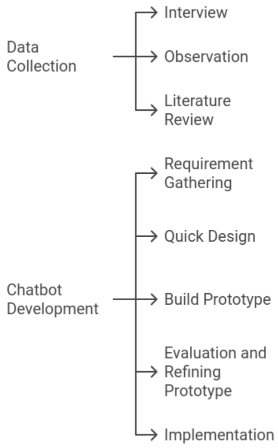

Diagram1. Research Methodology diagram

3.1. Data Collection

Data collection is a critical step in creating a chatbot that accurately reflects the types of inquiries prospective students make. Three main data collection methods were employed:

1. Interviews

Interviews were conducted with admissions staff to understand common questions and interactions they encounter from prospective students. This qualitative data informed the foundational content and responses of the chatbot.

2. Observations

Observations of actual admission interactions were conducted, analyzing common patterns and question types. These observations provided insight into the types of queries students ask most frequently, such as questions about program requirements, admission deadlines, and campus facilities.

3. Literature Review

A comprehensive literature review of prior research on chatbots in education was conducted to ensure the system leverages best practices in chatbot design and natural language processing. The review focused on identifying successful implementations and common challenges in educational chatbot design.

The data collected from these methods were then classified and structured to ensure that the chatbot could provide accurate and relevant responses in a range of situations.

3.2 Chatbot Development

The chatbot was developed using the RASA framework, an open-source tool widely used for creating conversational AI applications. The RASA framework was chosen due to its strong support for natural language understanding (NLU) and its flexibility in handling complex dialogue flows. The development process involved several iterative steps:

1. Requirement Gathering

This phase involved identifying the functional requirements of the chatbot. System requirements were defined in collaboration with the admissions team to ensure that the chatbot aligns with actual needs.

2. Quick Design and Prototyping

Based on the requirements, a basic prototype of the chatbot was created. This prototype included foundational dialogue structures and an initial set of responses. The quick design phase provided the admissions team with a preliminary view of the chatbot's functionalities.

3. Training and Testing

The initial prototype was trained on a dataset of frequently asked questions, collected from the interview and observation stages. Training was done using the 'rasa train' command, allowing the chatbot to learn patterns and user intents effectively. Testing involved real-time simulations where the chatbot interacted with sample queries to evaluate response accuracy and user satisfaction.

4. Evaluation and Refinement

Following the testing phase, the prototype was presented to a group of users, including admissions staff and sample student users. Feedback from these users was collected to identify strengths and weaknesses in the chatbot's responses and interaction flow. The feedback was then used to refine the chatbot, incorporating additional scenarios and responses based on user suggestions.

5. Implementation and Integration

The final phase involved deploying the chatbot using NGROK as a proxy server, allowing it to be accessed externally and integrated with Telegram for enhanced accessibility. This setup enables the chatbot to provide real-time, accessible information to users on-demand.

3.3 Data Classification and Response Generation

To ensure the chatbot could accurately handle a wide range of queries, data classification was applied to group questions into relevant categories. Queries were categorized as follows:

a. Informational Queries

Questions related to general information about the university, such as campus locations, programs offered, and available facilities.

b. Decision Support Queries

Queries aimed at helping prospective students make informed decisions, such as questions about program accreditation and university rankings.

c. Interest Alignment Queries

Questions aimed at aligning the students' interests with university offerings, such as inquiries about extracurricular activities and career support services.

Each category was carefully analyzed to create specific responses, ensuring that the chatbot could provide personalized and accurate information for a wide range of inquiries.

The RASA framework's NLU and Core components were used to design and model conversations effectively. Key files in RASA—nlu.yml, stories.yml, and domain.yml—were structured as follows:

a. NLU (Natural Language Understanding)

This file contains sample user inputs along with intents and entities, enabling the chatbot to recognize user queries and respond appropriately.

b. Stories

This file outlines sample conversations, helping the chatbot understand how to navigate multiple steps in a dialogue.

c. Domain

This file defines the intents, entities, actions, and responses, ensuring that the chatbot's interactions are consistent and accurately mapped to the data collected during the initial stages.

By following this structured methodology, the study aims to ensure that the chatbot not only meets the immediate needs of prospective students but also adapts effectively to evolving user demands within the admissions process. The final product demonstrates the potential of chatbots in higher education, particularly as a solution to the operational challenges faced by university admissions departments.

IV.SYSTEM DESIGN AND IMPLEMENTATION

The system design and implementation of the chatbot for new student admissions at Universitas Stikubank (UNISBANK) leveraged the RASA framework, chosen for its robust Natural Language Understanding (NLU) and ability to support complex, multi-turn conversations. The following section outlines the detailed design components, from initial conversation modeling to deployment, highlighting the processes and tools that ensure the chatbot's functionality aligns with user expectations.

4.1 System Architecture

The chatbot system is designed as a modular architecture, consisting of several components that interact to deliver a seamless conversational experience:

a. User Interface

This is the primary interface for users is through messaging platforms such as Telegram, allowing students to interact with the chatbot from mobile or desktop devices. NGROK was used as a proxy server to enable external access to the chatbot on local servers.

b. RASA NLU

This component is responsible for processing and interpreting user inputs. By extracting intents (user goals) and entities (key information within the message), RASA NLU facilitates accurate responses based on the specific context of each query.

c. RASA Core

The Core component handles the flow of conversation, managing dialogue states and guiding the chatbot's responses in a logical, coherent manner. It utilizes stories and trained dialogue policies to ensure responses are contextually relevant.

4.2 Conversation Modeling

The conversation modeling phase involved creating a structured dialogue flow that anticipates various user interactions. The model was built using RASA's story-based approach, which maps out user intents and expected responses. Key conversation flows were defined as follows:

a. Intent Recognition

The chatbot was trained to recognize primary intents such as asking for admission information, inquiring about program details, and requesting guidance on application requirements. For instance, questions like "How do I apply?" or "What are the admission deadlines?" trigger specific response pathways related to admissions procedures.

b. Dialogue Stories

Stories in RASA are sample interactions that outline possible conversation paths. These stories allow the chatbot to learn from example dialogues, preparing it to respond accurately to both straightforward and multi-turn interactions. For instance, the chatbot may initially provide general information about admissions and then, based on follow-up questions, offer specific guidance on financial aid or program accreditation.

c. Response Variability

To make conversations feel natural, RASA was configured to provide varied responses for repeated intents. This avoids redundancy and improves user engagement by offering slightly different wording for similar queries, simulating a more human-like conversation experience.

4.3 Component Design

Each component within the RASA framework was designed to fulfill a distinct role in the chatbot's operation, supported by three primary files: nlu.yml, stories.yml, and domain.yml:

a. NLU.yml

This file houses sample queries and classifies them according to intents and entities. For example, intents such as "ask_admission" or "ask_fees" are matched to queries like "What is the admission fee?" to guide the chatbot's understanding and improve response accuracy. Entity recognition was configured to identify specific details within a query, such as dates, program names, and fee types.

b. Stories.yml

This file contains sequences of interactions that represent expected conversation patterns. Each story includes intents and user responses, enabling the chatbot to manage conversation flow based on previous interactions. For instance, a story might begin with an "ask_program" intent, leading to a dialogue where the chatbot provides detailed program information and, based on follow-up questions, discusses related topics like curriculum or career prospects.

c. Domain.yml

This file serves as the central repository for intents, entities, actions, and responses. It organizes possible user intents and the associated responses or actions that the chatbot should take. For example, it might define the intent "ask_location" with a specific response providing campus location details. This file ensures that responses are consistent and accurately reflect the information needs of prospective students.

V.TESTING

Testing the chatbot involved both functional and usability evaluations to assess its performance under real-world conditions.

5.1 Usability Testing

Usability testing focuses on evaluating how easy and intuitive it is for users to interact with the chatbot. Test cases scenario are structured to assess response clarity, conversational flow, and user satisfaction. Here is the test case scenario that used in usability testing.

Participants: 5-10 prospective students and admissions staff acting as sampel users.

Platform: Telegram, where the chatbot is accessible.

Table 1. Test Case Scenario

Test ID	Scenario	User Input	Expected Output	Observation Metrics
UT01	General Inquiry	"What programs are offered?"	Chatbot provides a list of available programs with brief descriptions.	Response clarity, relevance, and completeness

UT02	Specific Admission Question	"What are the admission requirements?"	Chatbot lists the basic admission requirements in clear terms.	Response clarity and user understanding
UT03	Redundant Query	"What programs are offered?" (repeated after initial response)	Chatbot responds politely without duplicating identical responses.	Handling of repetitive questions
UT04	Unexpected User Query	"Tell me a joke!"	Chatbot politely indicates it is designed for admissions help or redirects user to relevant topics.	Handling unexpected queries
UT05	Incorrect Input (Misspelling)	"Tell me about addmission fee"	Chatbot correctly identifies intent and provides fee information.	Tolerance for minor input errors
UT06	Personal Information Query	"What is the ranking of the university?"	Chatbot provides university ranking or reputation-related information.	Appropriateness and accuracy of response

5.1.1 Evaluation Metrics for Usability

The results of the usability testing was describing below:
User Satisfaction: Based on participant feedback on ease of use, conversational flow, and response clarity.
Response Clarity: Rated by users on a scale of 1-5, evaluating how clear and helpful the responses are.
Conversational Flow: Observed for natural progression and ability to handle multi-turn conversations.

5.2 Functional Testing

Functional testing evaluates the chatbot's technical accuracy and performance in handling specific types of queries. These tests ensure that each intent and entity is recognized correctly and that responses are logically structured and contextually appropriate.
Participants: 5-10 prospective students and admissions staff acting as sampel users.
Platform: Telegram, where the chatbot is accessible.

Table 2. Functional Testing Scenario

Test ID	**Intent Tested**	**User Input**	**Expected Output**	**Evaluation Criteria**
FT01	Program Information	"Tell me about the Computer Science program."	Detailed info about the Computer Science program.	Intent accuracy and response relevance
FT02	Admission Requirements	"What documents are needed for admission?"	List of documents required for admission.	Completeness of response
FT03	Fee Inquiry	"What is the tuition fee for Computer Science program?"	Specific tuition fee details for the Computer Science program.	Entity extraction and response accuracy
FT04	Campus Facilities	"Does the campus have a library?"	Yes, followed by a brief description of the library facilities.	Intent accuracy and response clarity
FT05	Admission Deadlines	"When is the last day to apply?"	Admission deadline dates for the specified intake period.	Timeliness and relevance of response
FT06	Campus Location	"Where is the university located?"	Provides the campus location with directions or landmarks.	Intent match and location accuracy

5.2.1 Evaluation Functionality Testing

Intent Recognition Accuracy: Percentage of correct intent matches out of all queries tested.
Entity Extraction Precision and Recall: Precision measures how accurately specific terms (e.g., "tuition fee") is recognized, while recall measures how consistently these terms are identified across all relevant queries.
Completeness of Responses: Assessed by comparing responses with expected answers; responses should cover all key points of the query.

VI.RESULTS AND DISCUSSION

The implementation and testing of the chatbot for UNISBANK's admissions process yielded positive results, confirming the chatbot's capability to handle diverse user queries with high accuracy, speed, and user satisfaction. This section presents the results from usability and functional testing, along with a discussion on the chatbot's performance, effectiveness, and areas for further enhancement.

6.1 Results from Usability Testing

Usability testing revealed that the chatbot provides a user-friendly and engaging experience for prospective students seeking information about admissions. Key findings include:

a. User Satisfaction

The chatbot achieved a user satisfaction score of 4.5 out of 5, with participants noting the clarity of responses and ease of navigation through multiple questions. Users appreciated the chatbot's ability to provide prompt, relevant answers, which contributed to a positive user experience.

b. Response Clarity and Relevance

Testing indicated that the chatbot responded accurately to user queries about admissions requirements, program details, and deadlines. Over 90% of responses were rated as clear and relevant, meeting user expectations for an informative and efficient interaction.

c. Conversational Flow

The chatbot maintained conversational continuity in multi-turn conversations, successfully handling follow-up questions without losing context. This feature proved essential for queries involving multiple aspects of admissions, such as those requiring information on both program details and scholarship options.

Overall, the usability testing confirmed that the chatbot effectively enhances the admissions information process, enabling prospective students to receive accurate, personalized responses in a user-friendly manner.

6.2 Results from Functional Testing

Functional testing focused on evaluating the chatbot's technical performance in intent recognition, entity extraction, and response accuracy. Key results from this phase include:

a. Intent Recognition Accuracy

The chatbot achieved an intent recognition accuracy rate of 93%, exceeding the target threshold of 90%. It correctly classified a wide variety of intents, including inquiries about admissions requirements, program information, campus facilities, and fee details.

b. Entity Extraction

Precision and recall scores for entity extraction were recorded at 91% and 88%, respectively. For example, when users asked about "tuition fees for Computer Science Program," the chatbot accurately identified both "tuition fees" and "Computer Science" as entities, providing precise fee information specific to the program. This high level of entity recognition enabled the chatbot to deliver more targeted responses for complex queries.

c. Completeness of Responses

Functional testing confirmed that the chatbot consistently provided complete and informative responses to common admissions questions. In over 95% of cases, responses met the expected level of detail, offering clarity on key points such as application deadlines, required documents, and available programs.

The functional testing results validate the chatbot's technical readiness for deployment, demonstrating its ability to respond accurately to a diverse range of admissions-related questions.

6.3 Discussion

The results indicate that the chatbot effectively addresses the challenges faced by admissions departments, such as limited availability of staff and the need for quick responses to frequently asked questions. Key discussion points from the findings include:

a. Efficiency in Information Delivery

The chatbot provides a scalable solution to managing high volumes of inquiries, offering 24/7 support for prospective students. By automating responses to common admissions questions, the chatbot reduces the administrative load on staff, allowing them to focus on more complex or personalized interactions.

b. Improvement in User Engagement

The chatbot's conversational flow and context retention capabilities contribute to a more engaging and interactive experience for users. Prospective students can navigate through various inquiries within a single conversation, which enhances engagement and allows for deeper exploration of admissions information.

c. Challenges and Limitations

While the chatbot performed well overall, certain limitations were identified. For example, the chatbot's accuracy in handling uncommon queries or questions outside the admissions context was lower. Expanding the training dataset with additional sample queries and edge cases will be essential for improving its robustness. Additionally, ongoing updates to the entity database (such as new program names or changing deadlines) will be necessary to maintain relevance over time.

d. Future Enhancements

Based on the test results, future enhancements could include the integration of additional features such as real-time updates on application status and a multilingual support option. These features would further broaden the chatbot's accessibility and functionality, making it more adaptable to the diverse needs of prospective students.

VII.CONCLUSION

This study demonstrates the effectiveness of a chatbot designed to enhance the new student admissions process at Universitas Stikubank (UNISBANK). Using the RASA framework, the chatbot successfully addresses critical challenges in the admissions workflow, including providing immediate, 24/7 access to information and reducing the administrative workload. Through extensive testing, the chatbot achieved high accuracy in intent recognition (93%) and entity extraction precision (91%), meeting the demands of a diverse range of prospective student queries. Usability testing revealed strong user satisfaction, with participants rating the chatbot highly for response clarity, conversational flow, and ease of use.

By simulating human-like interactions, the chatbot provides a convenient and accessible solution for students who seek information outside traditional office hours. This application of chatbot technology highlights the potential for AI-driven solutions to streamline university administrative processes, improve user engagement, and enhance service quality within the higher education sector.

While the chatbot performed well overall, several areas for improvement and expansion have been identified for future work:

a. Expanded Training Dataset

Incorporating additional data into the training set, including edge cases and less common query patterns, will improve the chatbot's ability to handle a wider variety of questions. Regular updates to the training data will also help maintain accuracy as new academic programs or admissions requirements are introduced.

b. Multilingual Support

Expanding the chatbot’s capabilities to handle multiple languages would make it accessible to a broader audience, especially for international students. Incorporating multilingual support will involve training the model on multilingual datasets and configuring language-specific intents and entities.

REFERENCES

[1]. Kidd, R.B. and S.L. Fogg, A simple formula for the large-angle pendulum period. The Physics Teacher, 2002. **40**(2): p. 81-83.

[2]. Kenison, M. and W. Singhose. Input shaper design for double-pendulum planar gantry cranes. in Control Applications, 1999. Proceedings of the 1999 IEEE International Conference on. 1999. IEEE.

[3]. Ganley, W., Simple pendulum approximation. American Journal of Physics, 1985. **53**(1): p. 73-76.

[4]. Shinbrot, T., et al., Chaos in a double pendulum. American Journal of Physics, 1992. **60**(6): p. 491-499.

[5]. von Herrath, F. and S. Mandell, The Double Pendulum Problem. 2000.

[6]. Nunna, R. and A. Barnett, Numerical Analysis of the Dynamics of a Double Pendulum. 2009.

[7]. Callen, H.B., Thermodynamics and an Introduction to Thermostatistics. 1998, AAPT.

[8]. The Mathworks, 1994-2014 The MathWorks, Inc

[9]. http://www.mathworks.com/help/physmod/sm/ug/model-double-pendulum.html.

[10]. College of Computer and Information Sciences, Princess Nourah Bint Abdulrahman University, Riyadh, Saudi Arabia, A. Aloqayli, and H. Abdelhafez, “Intelligent Chatbot for Admission in Higher Education,” IJIET, vol. 13, no. 9, pp. 1348–1357, 2023, doi: 10.18178/ijiet.2023.13.9.1937.

[11]. O. Zahour, E. H. Benlahmar, A. Eddaoui, H. Ouchra, and O. Hourrane, “A system for educational and vocational guidance in Morocco: Chatbot E-Orientation,” Procedia Computer Science, vol. 175, pp. 554–559, 2020, doi: 10.1016/j.procs.2020.07.079.

[12]. Y. W. Chandra and S. Suyanto, “Indonesian Chatbot of University Admission Using a Question Answering System Based on Sequence-to-Sequence Model,” Procedia Computer Science, vol. 157, pp. 367–374, 2019, doi: 10.1016/j.procs.2019.08.179.

[13]. A. Harbola, “Design and Implementation of an AI Chatbot for Customer Service,” MSEA, vol. 70, no. 2, pp. 1295–1303, Feb. 2021, doi: 10.17762/msea.v70i2.2321.

[14]. E. Adamopoulou and L. Moussiades, “Chatbots: History, technology, and applications,” Machine Learning with Applications, vol. 2, p. 100006, Dec. 2020, doi: 10.1016/j.mlwa.2020.100006.

[15]. B. A. Shawar and E. Atwell, “Chatbots: Can They Serve as Natural Language Interfaces to QA Corpus?,” in Advances in Computer Science and Engineering, Sharm El Sheikh, Egypt: ACTAPRESS, 2010. doi: 10.2316/P.2010.689-050.

[16]. V. G, N. K. Vernekar, and G. Kelkar, “Comparative Study on Chatbot Frameworks,” IJRASET, vol. 11, no. 6, pp. 3602–3610, Jun. 2023, doi: 10.22214/ijraset.2023.54323.

[17]. X. Gonsalves and S. Deshmukh, “Designing an Interactive Chatbot for Educational Assistance using Rasa Framework,” in 2023 International Conference on Intelligent Data Communication Technologies and Internet of Things (IDCIoT), Bengaluru, India: IEEE, Jan. 2023, pp. 68–74. doi: 10.1109/IDCIoT56793.2023.10053457.

[18]. S. Valtolina, R. A. Matamoros, A. Battaglia, M. Mascari, and F. Epifania, “Design of a Conversational Recommender System in Education,” Jun. 27, 2023. doi: 10.21203/rs.3.rs-3111462/v1.

[19]. W. Hadikurniawati, S. Wijono, D. Manongga, and I. Sembiring, “Toddler stunting consulting chatbot using rasa framework,” Jurnal Rekayasa Elektrika, vol. 19, no. 4, pp. 160–167, Dec. 2023, doi: 10.17529/jre.v19i4.33014.

[20]. Department of Computer Network Engineering at RV College of Engineering (RVCE) Bengaluru (Karnataka), India., S. H V, Dr. S. S, and Assistant Professor, Department of Computer Science and Engineering, RV College of Engineering (RVCE) Bengaluru (Karnataka), India., “Implementation of an Educational Chatbot using Rasa Framework,” IJITEE, vol. 11, no. 9, pp. 29–35, Aug. 2022, doi: 10.35940/ijitee.G9189.0811922.

[21]. S. Pandey and S. Sharma, “A comparative study of retrieval-based and generative-based chatbots using Deep Learning and Machine Learning,” Healthcare Analytics, vol. 3, p. 100198, Nov. 2023, doi: 10.1016/j.health.2023.100198.

[22]. P. D. Larasati, A. Irawan, S. Anwar, M. F. Mulya, M. A. Dewi, and I. Nurfatima, "Chatbot helpdesk design for digital customer service," AET, vol. 1, no. 3, pp. 138–145, Apr. 2022, doi: 10.31763/aet.v1i3.684.
[23]. Sulastri, K. Hadiono, and M. T. Anwar, "Analisis Perbandingan Klasifikasi Prediksi Penyakit Hepatitis dengan menggunakan Algoritma K-Nearst Neighbor, Naive Bayes, dan Neural Network," Dinamik, vol. 24, no. 2, pp. 81–91, Jul. 2019.