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Research paper

Implementing Bidirectional Encoder Representations from Transformers and Gated Recurrent Units in a Chatbot for Student Support Services

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Abstract

Establishing efficient communication among students, faculty, and administrators is imperative to the effective operation of educational institutions. Understanding students' expectations for fast, flexible, and personalized access to support services can improve satisfaction and strengthen institutional performance. The increasing demand for prompt solutions in question–and–answer services has led to the emergence of intelligent automation, particularly AI–powered chatbots, to address existing educational challenges. This study developed and evaluated a web–based student support system featuring a chatbot that integrates Bidirectional Encoder Representations from Transformers (BERT) and Gated Recurrent Units (GRU) to enhance student support services. The NLP–driven chatbot provides real–time, automated responses to student inquiries, such as enrollment, schedules, tuition, and academic policies. Experimental results showed that the BERT model effectively identified user intent, achieving precision, recall, and F1 scores of 0.87 and above. The GRU–based decoder generated coherent and contextually relevant replies, validated through ROUGE metrics. Usability testing based on ISO 9241–11:2018 yielded mean scores above 4.5, confirming the system's effectiveness and user satisfaction. Overall, the BERT–GRU chatbot demonstrates a practical and scalable solution for providing 24/7 student assistance and improving institutional support. Recommendations were proposed to enhance the implementation, effectiveness, and future development of BERT–GRU chatbot systems in educational settings.

Keywords: *BERT; GRU; NLP; Seq2seq Architecture; Domain–Specific Chatbot; Student Support System; Contextual Understanding.*

1. Introduction

The persistent gap between student needs and available institutional support underscores the necessity for more responsive and accessible support mechanisms. The growing value of intelligent automation, particularly AI–powered chatbots, is becoming evident in addressing student support challenges (Martinez–Requejo et al., 2024; Oghenekaro & Okoro, 2024; Al–Abdullatif, 2023; Duduka et al., 2023). Chatbots can enhance educational services by extending availability and providing consistent, high-quality assistance for students (Benayache & Mourad, 2024; Pereira et al., 2023; Ramandanis & Xinogalos, 2023). Unlike basic FAQ tools or keyword–based bots, modern intelligent chatbots use advanced Natural Language Processing (NLP) to interpret questions, understand intent, and generate natural responses, significantly improving student experience while reducing academic staff workload (Mikael et al., 2025; Peyton et al., 2025; Attigeri et al., 2024; Hailu et al., 2024; Martinez–Requejo et al., 2024; Razak et al., 2024; Wang et al., 2023). Leveraging existing data with generative models and frameworks for student–focused chatbot development can help understand inquiries and provide answers aligned with user expectations (Kingchang, 2024; Modiba & Shekgola, 2024; Oliveira & Matos, 2023).

This study explored how two powerful models–Bidirectional Encoder Representations from Transformers (BERT) and Gated Recurrent Units (GRU)–can enhance a domain–specific, web–based student support chatbot system. The chatbot integrates BERT for contextual understanding and GRU for response generation. BERT is known for its deep contextual understanding of language and processes text bidirectionally, making it ideal for intent detection in student queries (Gardazi et al., 2025; Zhang et al., 2019; Devlin et al., 2018). To overcome BERT's input length and memory constraints, it was combined with GRU, which captures sequential dependencies within the text for context extraction and response generation (Bano et al., 2023). GRU is utilized in a Sequence–to–Sequence (Seq2Seq) approach to generate a response once the intent is captured (Wu et al., 2024). GRUs effectively handle conversational context, allowing the system to generate coherent and meaningful responses (Zhang et al., 2025; Lou et al., 2022; Noh, 2021). When integrated, these two models allow the chatbot to simulate human–like conversations while maintaining context understanding and speed. The domain–specific chatbot is designed to address common student concerns, such as admissions, schedules, deadlines, and campus services. It was integrated into a web platform so users could access it through a familiar institutional system. Chatbot responses were evaluated using the Recall–Oriented Understudy for Gisting Evaluation (ROUGE) metrics (Lin, 2004; Barbella & Tortora, 2022), and usability was assessed using ISO 9241–11:2018 (International Organization for Standardization, 2018).

By focusing on real student use cases in the Philippine educational setting, this study demonstrates how integrating BERT and GRU can support scalable student assistance, where such systems are still emerging (Peyton et al., 2025).

2. Literature Review

Natural Language Processing is crucial in human–computer interaction as it enables machines to understand, interpret, and generate human language. NLP applications continue to expand in the educational domain (Hurana et al., 2023; Rayhan, 2023; Shaik et al., 2022; Torfi et al., 2021), paving the way for conversational agents that provide interactive student assistance (Chandrawat & Researcher III, 2025; Karegowda et al., 2025; Oni, 2025; Ascama et al., 2024; Bhoyar, 2023).
Typically integrating into systems, AI–powered chatbots become a favorable solution to some of the existing educational issues by providing immediate support by answering questions, offering explanations, and providing relevant resources with minimal or no human intervention (Davis et al., 2025; Martinez–Requejo et al., 2024; Olujimi & Ade–Ibijola, 2023; Labadze et al., 2023; Pereira et al., 2023; Oghenekaro & Okoro, 2024; Al–Abdullatif, 2023; Duduka et al., 2023; Karyotaki et al., 2022). Chatbot integration delivers persistent educational support services among various stakeholders (Benayache & Mourad, 2024; Abdallah et al., 2024; Ramandanis & Xinogalos, 2023), including 24/7 support for students and real–time feedback (Davar et al., 2025; Modiba & Shekgola, 2024; Kooli, 2023; Mathew et al., 2021). Leveraging these NLP–based frameworks contributing to sustainable student support systems (Peyton et al., 2025; Sophia, 2025; Abdallah et al., 2024).
BERT and GRU are two influential NLP architectures. BERT's backward and forward approach captures deeper contextual understanding (Gardazi et al., 2025; Zhang et al., 2019; Devlin et al., 2018). Transformer, like BERT, adopts a fixed coding length scheme, dividing the long text into multiple segments and coding them separately (Han et al., 2022). This fixed input length constraint and shorter memory footprint require complementary methods for longer sequences (Bano et al., 2023; Han et al., 2022). GRU, a type of Recurrent Neural Network (RNN), captures long–term dependencies while using fewer parameters than Long Short–Term Memory (LSTM), enabling efficient sequential processing (Gao et al., 2021; Yiğit & Amasyali, 2021). Integrating GRU with BERT helps overcome BERT's sequence limitations (Gardazi et al., 2025; Ding et al., 2020), effective for educational chatbots that require context handling. Since BERT has a maximum token limit (typically 512 tokens), which can be limiting for certain tasks that require processing longer contexts, the chatbot framework combined it with GRU to capture sequential dependencies within the text for context extraction and response generation. GRU performs well in cases of long and low–complexity sequences of small datasets, suitable for the chatbot system developed in a domain–specific setting (Cahuantzi et al., 2023; Yang et al., 2020; Chung et al., 2014).
Several studies combined BERT and GRU or the variant architectures for word contextualization and question classification (Sultani & Daneshpour, 2025; Tian, 2023; Han et al., 2022; Khodeir, 2021; Zhang & Xing, 2021), sentiment analysis (Jayakumar et al., 2024; Yao & Bi, 2024; Zhang et al., 2023; Horne et al., 2020), summarization (Bano et al., 2023; Sana & Akhtar, 2023), and relation extraction (Yi & Hu, 2020). These underscore the effectiveness of BERT–GRU model in question–and–answer related tasks, a novel approach to contextual conversational chatbot systems for educational settings. The BERT–GRU model further refines the context–aware, consistent response with enhanced memory directions of chatbot systems focused on student support services (Oni, 2025; Jayakumar et al., 2024).

3. Methods

3.1. Research Design and Procedures

Developmental research was employed to design, develop, and evaluate the web–based student support system featuring a BERT–GRU chatbot. This research approach ensures that the system is grounded in real–world needs and iteratively refined through user feedback and testing.
To structure the development process, the study followed the ADDIE model, a framework used in instructional design and effective in educational chatbot development (Nugraha & Setiyawan, 2025). The ADDIE model supports a logical and iterative workflow, making it ideal for designing complex systems such as intelligent chatbots in education (Branch, 2010; Molenda, 2003). The design ensured that the web–based student support system, featuring a BERT–GRU chatbot, aligns with the specific needs of the local clientele. The research followed the systematic five–phase procedure based on the ADDIE model:
Analysis Phase. The study examined existing support workflows and common student concerns through service logs, interviews, and observations involving administrators and students. To ensure alignment with data protection policies, no sensitive data was collected, and informed consent was obtained from participating stakeholders regarding data management throughout the process. The results informed system requirements and the selection of models and technologies.
Design phase. The system and chatbot workflow were mapped, including user interaction flows, intent categories, and the integration of BERT and GRU. As shown in Fig. 1, the chatbot architectural framework of the chatbot system.

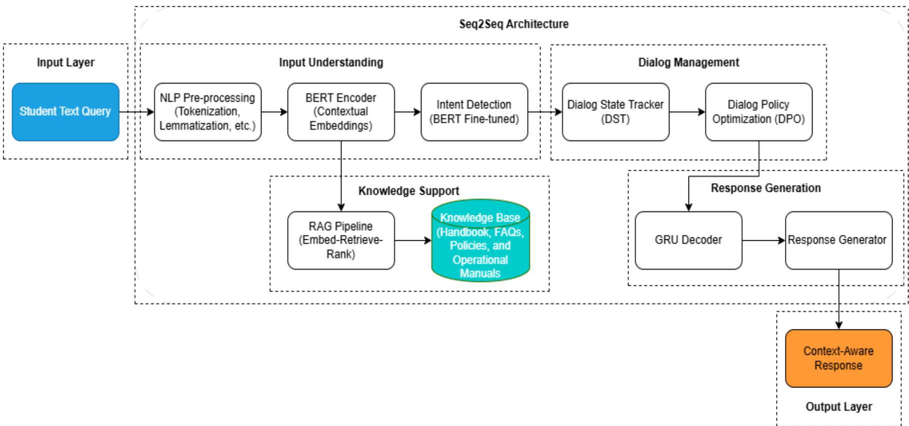

Fig. 1: BERT–GRU Chatbot Architecture.

It was designed to utilize the fine–tuned BERT to encode deep contextual representations of the input and GRU to encode the sequence and decode the output step–by–step. Driven by the BERT encoder and GRU decoder, the Seq2Seq architecture facilitates the mapping of an input sequence to an output sequence, generating coherent and contextually relevant responses

The web–based student support system was also designed to cover the major student support services of the locale, which include Records and Admissions, Guidance, Health, and Library services. Design tools were developed to guide the planning and development of the web–based student support system featuring the BERT–GRU chatbot. The website structure, shown in Fig. 2, illustrates the major functions of each access account in the developed system.

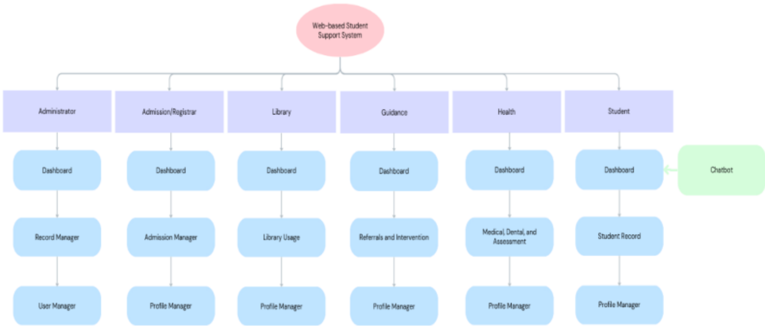

Fig. 2: Student Support Services Website Structure.

Development Phase. The system was developed using XAMPP, Laravel (MVC), Tailwind CSS, and Laravel Breeze. The chatbot was implemented in Python using fine–tuned BERT for intent recognition and a GRU–based Seq2Seq decoder for response generation. Training data were curated from real student queries and institutional guidelines.

Implementation Phase. The system was deployed on AWS Lightsail. Orientation sessions introduced users to its features, while usage logs captured real–time feedback and performance.

Evaluation Phase. Chatbot responses were evaluated using ROUGE metrics, while usability was assessed using the ISO 9241–11:2018 framework. Open–ended feedback further informed improvements.

Implementing the ADDIE model permitted the researchers to continuously improve the web–based student support chatbot system at every stage, ensuring the chatbot system is functional and easy to use for the educational community.

3.2. Research Instrument and Sources of Data

The study used a structured instrument integrating objective performance metrics and user feedback. ROUGE evaluated the accuracy of chatbot responses (Barbella & Tortora, 2022; Lin, 2004). Usability was measured using a 5–point Likert scale based on ISO 9241–11:2018 (Lewis & Sauro, 2021; International Organization for Standardization, 2018; Bevan et al., 2015) and chatbot usability criteria (Følstad & Brandtzaeg, 2020).

3.3. Statistical Treatment of Data

ROUGE–N and ROUGE–L metrics assessed response accuracy. Usability results were analyzed using mean, frequency, percentage, and standard deviation to interpret user perceptions regarding effectiveness, efficiency, satisfaction, and context of use.

4. Result and Discussion

This section presents the results of chatbot development and discusses the findings in relation to the study's objectives.

4.1. Web–based system for student support services development

A functional and responsive web–based system was created to facilitate access to student support services through a chatbot interface. Fig. 3 shows the homepage of the web–based student support system, where accounts for administrators, staff, and students can navigate relevant student support services.

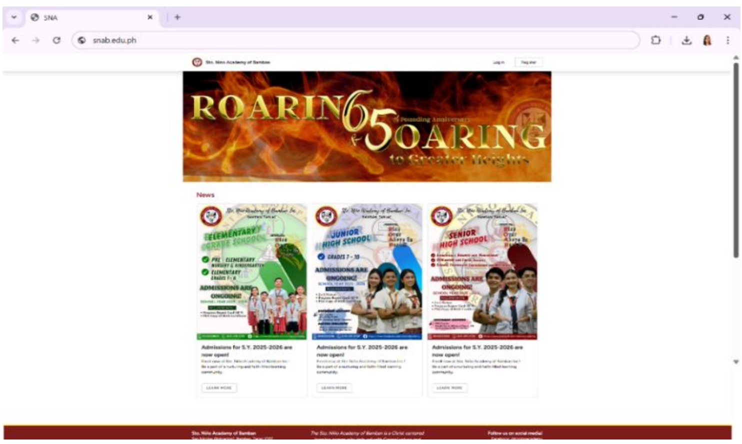

Fig. 3: Student Support Services Website Homepage.

4.2. NLP–driven chatbot integration

The BERT–GRU chatbot successfully interpreted student queries and generated relevant responses. Fig. 4 shows a sample chatbot interaction in the student account.

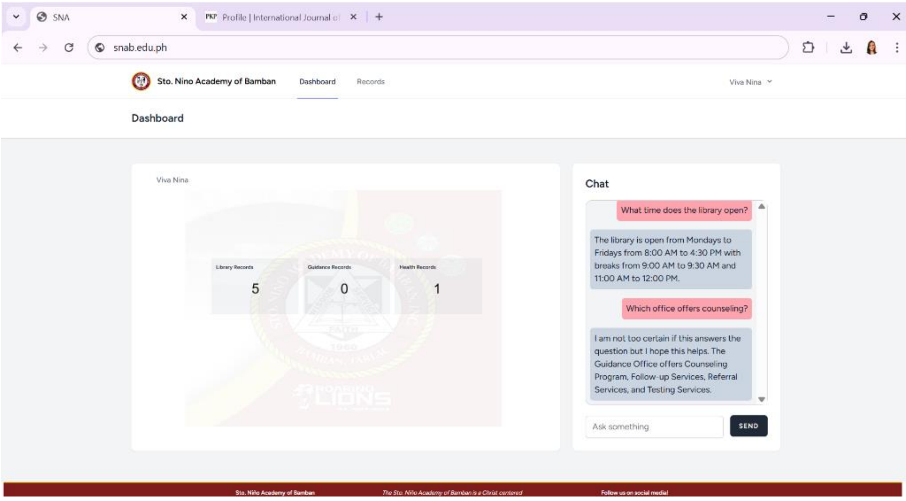

Fig. 4: Student Account Dashboard with Chatbot Interface.

The interaction is composed of three core layers: the user interaction, the NLP engine, and the output feedback loop. The user interaction layer facilitated the initial and final exchange between the student and the chatbot. The NLP engine employed BERT for context recognition and GRU for response generation. The output feedback loop collected feedback and query logs, allowing the system to be iteratively improved. Table 1 shows sample interactions demonstrating accurate intent detection and context–appropriate replies.

Table 1: Sample Student Queries and Chatbot Responses

Student Query	Detected Intent	Chatbot Response
How do I enroll for next semester?	Enrollment Inquiry	You can enroll through the student portal. Click on 'Enrollment' and follow the steps.
Can I get a copy of my report card?	Document Request	Yes, you can request your report card at the Registrar's Office or through the online form.
When does the class start?	Schedule Inquiry	Classes begin on June 10. Please check your portal for your specific schedule.
How much is the tuition for Grade 12?	Tuition Inquiry	Tuition for Grade 12 is listed in your student account on the portal.
Do we have class on Independence Day?	Holiday Schedule	No, there are no classes on national holidays, such as Independence Day.

The chatbot demonstrated the ability to process diverse queries from students across various service–related areas, such as enrollment, class schedules, documents, and tuition. These interactions validate the chatbot's capability to assist in the institution's operations by handling common repetitive queries that usually require human intervention.

4.3. BERT model implementation for contextual understanding

The BERT classifier demonstrated strong intent detection, achieving F1 scores of 0.88 and above across all categories, as shown in Table 2. These findings are consistent with previous studies reporting BERT's high performance in text classification (Devlin et al., 2019; Zhang et al., 2019).

Table 2: BERT Model Performance Result

Intent Category	Precision	Recall	F1 Score
Enrollment Inquiry	0.94	0.91	0.92
Document Request	0.93	0.90	0.91
Schedule Inquiry	0.92	0.89	0.90
Tuition Concern	0.91	0.88	0.89
General Policy	0.90	0.87	0.88

The implementation of the BERT model significantly enhanced the chatbot's ability to detect user intent and interpret message context. BERT served as the core of the chatbot's NLP engine. By using pretrained weights and fine–tuning on localized training data, the model became better aligned with institutional language patterns and support needs, minimizing potential bias.

4.4. Seq2seq GRU–based decoder utilization for response generation

The GRU decoder in the Seq2Seq architecture produced grammatically correct, contextually relevant responses, as shown in Table 3.

Table 3: Sample Student Queries and GRU–Generated Responses

Student Query	GRU–Generated Response
Where can I get my Form 137?	You can request your Form 137 from the Registrar's Office or via the online form.
Do we have class on holidays?	Classes are suspended on holidays declared by the government or the school administration.
How much is the tuition for Grade 11?	Please check your student portal under 'Billing' for your personalized tuition details.
When does the second semester start?	The second semester starts on November 5. Kindly check your schedule on the portal.
Can I wear casual attire on Fridays?	Students are allowed to wear casual attire on Fridays unless stated otherwise.

This aligns with prior research highlighting GRU's advantages in conversational applications (Cahuantzi et al. 2023; Yang et al., 2020; Chung et al., 2014).

4.5. Evaluation of chatbot response accuracy using ROUGE and usability using ISO 9241–11:2018

ROUGE results, as shown in Table 4, indicate high lexical similarity and coherent response flow.

Table 4: ROUGE Metrics Evaluation Results

ROUGE Metric	Mean Score	Interpretation	Comment
ROUGE–1	0.89	High lexical similarity	Word choices matched the reference answers effectively.
ROUGE–2	0.86	High bigram accuracy	Key phrases were consistently preserved.
ROUGE–L	0.87	Good sequence alignment	Sentence flow and logical structure were appropriate.

Table 5 shows the usability results based on ISO 9241–11:2018, which reveals "Very Satisfactory" ratings across all dimensions, indicating that the chatbot effectively supports users in real educational settings.

Table 5: Usability Evaluation Results

Usability Dimension	Mean	Interpretation
Effectiveness	4.6	Very Satisfactory
Efficiency	4.5	Very Satisfactory
Satisfaction	4.7	Very Satisfactory
Context of Use	4.6	Very Satisfactory

These findings align with prior studies emphasizing the importance of usability and system reliability in AI–powered academic tools (Følstad & Brandtzaeg, 2020), confirming that the chatbot is not only accurate in its responses but also effective in delivering a stable and accessible user experience.

Together, the ROUGE and 9241–11:2018 evaluations demonstrate that the BERT–GRU chatbot system successfully delivers accurate, human–like responses while maintaining high usability standards. These results validate the chatbot's readiness for real–world use and its potential to enhance student support services in Philippine academic institutions.

5. Conclusion

The study concludes that integrating BERT and GRU in a student support chatbot is both feasible and effective. The system was able to understand user intent, generate high-quality responses, and deliver strong usability outcomes. Results confirm that the chatbot can provide scalable, 24/7 assistance and enhance institutional support services.

Recommendations include further institutional integration, continuous dataset expansion, periodic model retraining, additional multimodal features, and replication in other schools to promote scalable educational AI solutions.

Conflict of Interest

The authors declare no conflict of interest.

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