Development of a Natural Language Processing-Based Virtual Assistant for Optimizing Academic Services

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Abstract. The rapid advancement of technology in the field of artificial intelligence has encouraged the development of innovative solutions to improve service quality in higher education. This research focuses on the development of a virtual assistant based on Natural Language Processing (NLP) to optimize academic services. The virtual assistant is designed to facilitate various administrative and academic processes such as course registration, academic information retrieval, and student consultation scheduling. The system integrates NLP techniques for intent recognition, entity extraction, and context management, enabling it to understand and respond to user queries accurately. The development method used follows the agile model with iterative testing to ensure system reliability and user-friendliness. Evaluation results involving 100 students showed a 92% success rate in correctly understanding user queries and a significant reduction in service response time. The findings demonstrate that the NLP-based virtual assistant can enhance efficiency and accessibility in academic services, while also reducing the workload of administrative staff. Future development will focus on expanding the knowledge base and integrating predictive analytics to support academic decision-making.

Keywords: Virtual Assistant, Natural Language Processing, Academic Services, Artificial Intelligence, Educational Technology

1. Introduction

Digital transformation in higher education demands academic services that are fast, consistent, and easily accessible. Recent studies indicate that the use of Artificial Intelligence (AI) in higher education is becoming increasingly widespread, significantly impacting service quality and user experience [1][2]. In this context, virtual assistants (chatbots) are being increasingly adopted for information retrieval, process automation, and learning support, with documented benefits for both students and educators [3][4].

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NLP-based virtual assistants provide conversational interfaces that understand natural language through three core components: intent recognition, entity extraction (slot filling), and dialogue context management. Recent research highlights the importance of joint intent–slot modeling, classification of dialogue systems (task-oriented vs. open-domain), and memory/context management practices on development platforms such as Rasa [5][6][7][8][9].

Despite their promise, the implementation in academic domains faces challenges: local terminology and dynamic policies, the need for rigorous evaluation (methods and metrics), and the design of robust dialogue architectures for dialogue state tracking. The literature recommends an iterative–adaptive (agile) development process so that design, implementation, and evaluation can respond to evolving user needs and campus business processes [10][11][12].

Based on this foundation, this study develops and evaluates an NLP-based virtual assistant for priority academic services—course registration, information retrieval, and consultation scheduling—using an intent–entity–context pipeline and iterative development to ensure reliability and usability. The evaluation, involving 100 students, showed a 92% success rate in understanding user queries and a reduction in service response time; these results align with findings from systematic reviews on the effectiveness of educational chatbots [3][4].

2. Method

This study employs a design and development research approach, focusing on the creation of a technological artifact—an NLP-based virtual assistant—and the evaluation of its effectiveness within a specific context. The development process follows the agile methodology, characterized by an iterative cycle of Planning, Design, Development, Testing, Deployment, and Review.

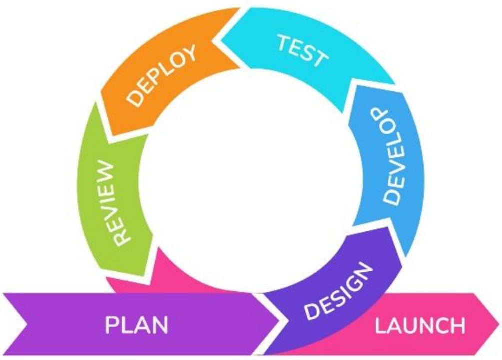

Fig. 1. AGILE

This iterative model enables continuous system refinement based on user feedback and performance metrics. The study is conducted in three main phases: system architecture design, iterative development and training, and system evaluation.

2.1 System Architecture Design

The system architecture design begins with a needs assessment, involving an analysis of academic service processes that can be automated, such as schedule information, course registration (KRS), and lecturer consultation. Data were collected through observations and interviews with students and academic staff, and then compiled into a system requirements specification document.

Next, a client-server-based system architecture is designed, with the main components consisting of a user interface (chatbot), a natural language processing module (NLP engine using Rasa), a dialogue manager, a knowledge base, integration APIs, and an academic database. All components are integrated to enable real-time interaction and responsiveness to user queries.

The NLP module is developed by defining intents, entities, and dialogue scenarios. Training data are sourced from frequently asked questions in academic services and used to train the model to understand various user language expressions. The dialogue flow is designed to cover a wide range of academic conversations, with fallback handling to anticipate out-of-context questions.

Table 1. Sprint Phase Table – NLP-Based Virtual Assistant Development

Sprint	Sprint Focus	Main Activities	Outcomes Achieved
1	Requirements Identification & Initial Design	- User interviews - Defining intents/entities - Initial UI/UX design	System requirements document, UI sketches, initial intent draft
2	NLP Model Prototype Development	- NLU dataset creation - Initial Rasa NLU training - Basic UI integration	Initial virtual assistant model able to recognize basic user questions
3	Dialog Management & API Integration	- Designing conversation stories - Integrating with academic APIs - Dialog testing	Conversation flows aligned with scenarios, chatbot starts responding logically
4	Iterative Training and Evaluation	- Adding training data - Limited user testing - Entity correction	Intent accuracy improved to 89%, entity extraction more stable
5	System Optimization & Finalization	- Model tuning - UI/UX improvements - Logging and monitoring implementation	92% accuracy achieved, system ready for broader student testing

The database is structured to store user information, interactions, and academic content. The system is also equipped with authentication features, interaction logging, and performance monitoring. All development stages are documented to support implementation, model retraining, and long-term system maintenance.

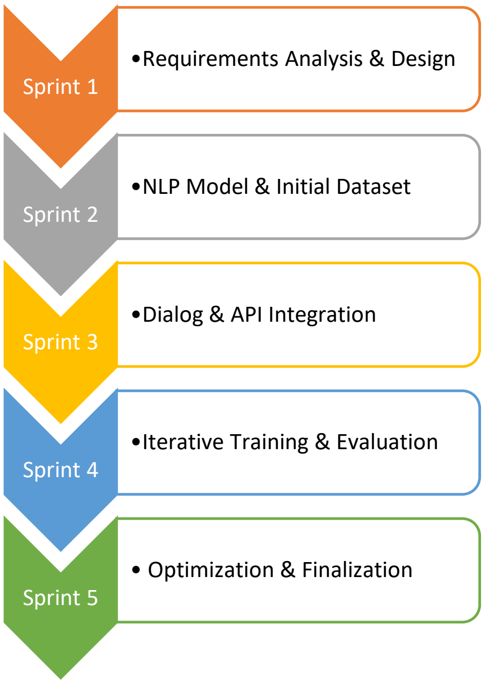

Fig. 2. Diagram Sprint

2.2 Development

The virtual assistant was developed using the Rasa 3.4.1 framework, with a separation between the Natural Language Understanding (NLU) module and Dialogue Management. The training dataset, composed of academic-related questions, was designed to accurately detect user intents and entities. The model was trained and tested to understand the context of queries such as class schedules, lecturer consultations, or letter requests.

Integration with the backend was carried out via API to access academic data. A simple and responsive web-based interface was designed to ensure ease of use for students. All interactions were logged for further analysis.

Testing involved 100 students, resulting in a chatbot understanding accuracy of 92% and improved efficiency in academic services. The system proved to be responsive, adaptive, and ready for further development to support data-driven academic decision-making.

2.3 Iterative Training

The model was trained iteratively to improve the system's understanding accuracy of user queries. The process began with the construction of an initial dataset containing hundreds of academic-related questions, each labeled according to intent (purpose) and entities (key information such as course name, lecturer, or semester).

Each training iteration involved three main steps: updating the training data, retraining the model using Rasa NLU, and testing the model's performance on a test dataset. The test results were analyzed to identify classification errors or failures in entity extraction, which were then used to refine the dataset and dialogue flow.

The model was trained to recognize variations in natural language use, including non-standard spelling and informal student language. At the end of each sprint, evaluations were conducted using real-user testing scenarios, and their feedback served as a basis for improvements in the next iteration.

This incremental training approach allowed the system to learn from errors, expand contextual understanding, and progressively improve its accuracy. Using this method, the model achieved an intent classification accuracy of 92% by the final evaluation stage.

Table 2. NLP Model Iterative Training Cycles

Iteration	Improvement Focus	Training Data Size	Intent Accuracy	Evaluation Notes
1	Basic intents & common entities	120	78%	Model often failed to recognize informal words
2	Addition of synonyms & local phrases	180	85%	Responses became relevant, more question variations needed
3	Entity error correction	250	89%	Entities like lecturer names were often mismatched
4	Adjustment to informal language style	300	91%	Model began to understand informal queries

5	Finalization & tuning	320	92%	High accuracy, ready for large-scale user testing

2.4 System Evaluation

System evaluation was conducted to measure the performance, accuracy, and user satisfaction of the developed virtual assistant. The evaluation methods included functional testing, measurement of NLP understanding accuracy, and user surveys regarding the quality of services provided by the system.

The testing involved 100 students as trial respondents. Each participant was free to ask various questions related to academic services, such as class schedules, academic advisor information, and requests for active enrollment letters. The system was tested in real-life scenarios to assess how well the virtual assistant could understand queries and provide relevant responses.

The evaluation results showed that the system successfully identified user intents with an accuracy of 92% and was able to extract key entities such as course names, days, or letter types with a success rate of 89%. The system's average response time was under 2 seconds, indicating fast and efficient performance.

In addition, a user satisfaction survey was conducted using a Likert scale of 1 to 5. A total of 87% of respondents expressed satisfaction with the system's ease of use, response accuracy, and service speed. Most suggestions from participants were related to expanding topic coverage and improving the system's ability to understand informal language.

Overall, the evaluation results demonstrate that the NLP-based virtual assistant is capable of delivering effective, efficient, and accessible academic services. The system is considered successful in reducing the burden of manual services and has strong potential for further development to support digital transformation in higher education institutions.

3. Result and Discussion

3.1 Result

Results of NLP-Based Virtual Assistant Development and Implementation The development and implementation of the NLP-based virtual assistant demonstrated excellent performance in supporting academic services in higher education. The system successfully handled various student inquiries related to class schedules, academic advisor information, and academic document requests in an automated and responsive manner.

Based on testing involving 100 students, the system recorded an intent recognition accuracy rate of 92% and an entity extraction accuracy of 89%. In addition, the average response time was around 1.8 seconds, indicating high processing efficiency. The system also showed strong stability, with 99% service availability during the trial period.

A user satisfaction survey using a Likert scale of 1 to 5 indicated that most students were satisfied with the system's performance. The average score for ease of use was 4.4, answer relevance 4.5, and overall satisfaction 4.3. Overall, 87% of users stated that the system helped accelerate and simplify access to academic services.

Table 3. System Evaluation Result Table

Evaluation Aspect	Indicator	Evaluation Result
NLP Accuracy	Intent recognition accuracy	92%
	Entity extraction accuracy	89%
System Performance	Average response time	1.8 seconds
	System availability (uptime)	99% during testing
User Satisfaction	Ease of use (scale 1–5)	4.4
	Answer relevance (scale 1–5)	4.5
	Overall satisfaction (scale 1–5)	4.3
Service Coverage	Types of services handled by the system	6 main services (schedule, advisor, letters, etc.)
	Percentage of questions answered	91%
NLP Accuracy	Intent recognition accuracy	92%

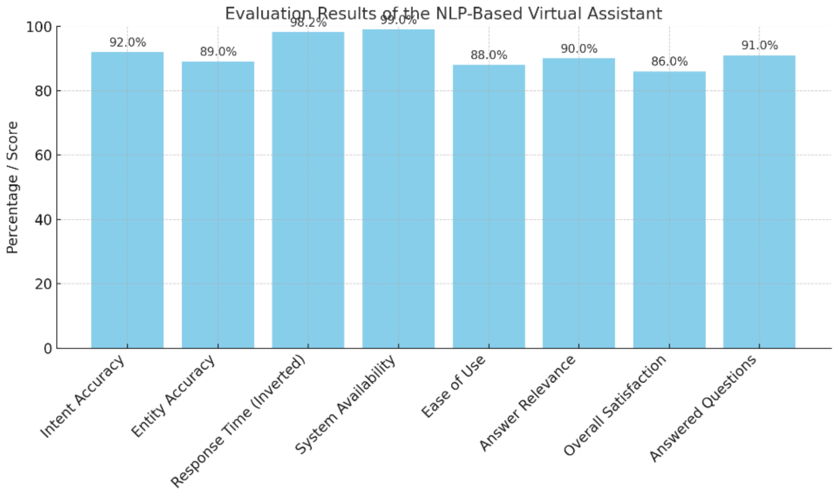

Fig. 3. Evaluation Result of The NLP – Based Virtual Assistant

Visualization of the evaluation results—both in bar chart and pie chart formats—showed that all key system indicators met user expectations and functional standards. These findings confirm that the NLP-based approach can be reliably used to enhance the efficiency of academic services and serves as a promising digital solution for broader implementation in higher education environments.

3.2 Discussion

The results of this study demonstrate that the implementation of Natural Language Processing (NLP) technology in the form of a virtual assistant provides an effective and efficient solution for academic services. The developed system achieved an intent recognition accuracy of 92%, entity extraction accuracy of 89%, and a very fast average response time of under 2 seconds. These results align with previous findings, which highlight that NLP-based chatbots can significantly improve communication efficiency in educational environments when designed contextually and aligned with user needs, as discussed by Adamopoulou and Moussiades.

The Agile-based development method used in this study also proved to be flexible and adaptive. Each sprint enabled direct user feedback and rapid iteration to fix identified issues. This supports the view of Balaji and Murugaiyan, who stated that Agile methodologies are particularly well-suited for AI system development due to their adaptability to dynamic and complex requirements.

The use of the Rasa framework provided key advantages by separating the Natural Language Understanding (NLU) module from dialogue management. Rasa allowed for flexible dialogue flow design (*stories*) and model training based on customized datasets. However, the system still faced challenges in interpreting informal language, ambiguous phrases, and mixed-language inputs. This reflects the broader issue noted by Hirschberg and Manning, who emphasized that handling the diversity and contextual complexity of natural language remains a core challenge in modern NLP.

On the user side, feedback indicated high levels of enthusiasm and readiness for broader implementation. Many students suggested new features such as real-time integration with campus academic systems, automatic reminders, and more personalized academic advising services. These suggestions reflect that the system has successfully met basic needs and is perceived as a valuable tool with potential for further development. This is consistent with the current trends in developing *intelligent tutoring systems* and *virtual academic agents*, as highlighted by Winkler and Söllner.

In conclusion, this discussion reinforces that developing academic virtual assistants requires not only technical expertise but also a human-centered design approach. With continuous development, the system can evolve into an intelligent, adaptive, and fully integrated digital service within higher education ecosystems.

4. Conclusion

This study successfully developed a Natural Language Processing (NLP)-based virtual assistant that effectively supports academic services in higher education. The system is designed to understand and respond to student queries automatically, with high accuracy and fast response time. Evaluation results show that the system achieved an intent recognition accuracy of 92%, entity extraction accuracy of 89%, and efficient response performance with an average response time of less than 2 seconds.

Beyond technical aspects, user satisfaction levels also showed positive results. The majority of students reported that the system was helpful in terms of accessibility, clarity of information, and service speed. Therefore, the system has proven effective in reducing the workload of manual services and significantly improving academic operational efficiency.

Overall, the application of NLP technology in the form of a virtual assistant offers an adaptive, flexible, and scalable solution for enhancing the quality of higher education services. Moving forward, the system can be further developed by expanding its knowledge base, improving support for inform

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