Implementing robo-advisory systems in virtual universities for smart student counselling

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Abstract: *The integration of AI-based advisory systems in higher education has transformed student advising by improving accessibility, efficiency, and accuracy. This study evaluates a GPT-based robo-advisory system designed to assist students with academic enquiries, administrative processes, and career advice. The system was trained on 29 module handbooks, general rules, and FAQs to ensure institution-specific accuracy. A test of 100 sample queries across different categories demonstrated 100% overall accuracy, reinforcing its reliability in providing correct and contextually relevant answers. Compared to traditional chatbots, the system excelled at interpreting complex queries, providing detailed academic insights, and streamlining university processes. In line with existing literature, the findings confirm that AI-driven advising improves student engagement and administrative efficiency, complementing previous research on chatbots in education. However, challenges remain, including the integration of predictive analytics, multilingual support, and ethical considerations, particularly when dealing with sensitive student issues. While the model successfully automates academic advising, it does not replace human advisors in cases that require emotional intelligence and ethical judgement. Addressing biases in AI-generated responses through refined training data and improving computational efficiency with scalable processing strategies are crucial for ensuring fairness and widespread implementation. Future developments should focus on hybrid models that combine AI-driven insights with human expertise to optimise student support. This study contributes to ongoing discussions about AI in higher education and advocates for adaptive, data-driven, and ethically responsible student advising systems.*

Keywords: Student Advising, Student Counselling, Virtual Universities, Artificial Intelligence, Robo-Advisory, ChatGPT.

1. Introduction

The rapid digital transformation of higher education has led to a significant increase in the use of virtual universities, online learning platforms, and digital student services (Mohamed Hashim, Tlemsani & Matthews, 2022; Rodríguez-Abitia & Bribiesca-Correa, 2021). As institutions expand their digital footprint, students often struggle to navigate complex academic structures, including course selection, exam requirements, administrative processes, and career planning.

https://doi.org/10.58503/icvl-v20y202517

Traditional student counselling services, while essential, are often overburdened, leading to delays, inefficiencies, and accessibility issues, especially for remote learners. Artificial Intelligence (AI) and Natural Language Processing (NLP) have emerged as transformative technologies that can improve student support services (Chatterjee & Bhattacharjee, 2020; Ouyang, Zheng & Jiao, 2022). Among these, chatbot systems powered by Generative Pre-trained Transformers (GPTs) represent a promising solution for intelligent student counselling, which is referred to in this article as robo-advisory (OpenAI, 2025). By integrating GPT models into student advisory services, institutions can provide immediate, contextualised, and personalised responses to students' queries about module handbooks, examination criteria, academic regulations, course requirements, and administrative procedures (Rawas, 2024; Sok & Heng, 2024). Despite the potential of AI-driven solutions, challenges remain in terms of implementation, accuracy, adaptability, and user adoption. Unlike rule-based chatbots, GPT-based robo-advisory systems require extensive training on institution-specific datasets, including course catalogues, university policies and procedural guidelines, to ensure reliability and trustworthiness (Lund & Wang, 2023; Sanderson, 2023). Furthermore, ethical concerns such as privacy, bias in recommendations and transparency need to be addressed. This study explores the development and implementation of a GPT-based robo-advisory system to serve as an intelligent academic assistant in virtual university environments.

The primary objective of this research is to develop and implement a GPT-based robo-advisory chatbot capable of providing real-time academic and administrative support to students in virtual universities. This study investigates the functional and technical aspects of integrating large language models (LLMs) into student support services. The research will focus on the concrete implementation and testing of the GPT-based advisory system to improve student support in virtual learning environments. Traditional university counselling often struggles with scalability, making AI-driven solutions essential to provide timely and accurate guidance. The study contributes to AI-driven education by integrating LLMs into academic counselling, addressing feasibility, challenges, and ethical considerations. Its findings will benefit educators, administrators, and researchers in developing scalable, student-centred AI advising solutions for digital education.

2. Literature review

The integration of AI-powered chatbots in higher education has gained significant attention, with multiple studies exploring their effectiveness in academic advising, student engagement, and administrative efficiency. Dibitonto et al. (2018) emphasise the importance of designing virtual assistants that enhance accessibility while maintaining user engagement and trust, a finding that aligns with Lucien and Park (2024), who demonstrate that the advising virtual assistant increased student interaction with academic resources but faced integration challenges. Similarly, Martinez-Requejo et al. (2024) report that chatbots

significantly improve student engagement and streamline university processes, complementing Barrett et al. (2019), who highlight the role of AI in enhancing course planning and communication efficiency. However, as Chen et al. (2023) note, these implementations must address concerns regarding accuracy, ethical considerations, and over-reliance on AI-based interactions.

From an academic advising perspective, Chun Ho et al. (2018) present EASElective, a chatbot that assists students in selecting elective courses, demonstrating that chatbots offer unique advantages over traditional advising services. This is reinforced by Akiba and Fraboni (2023), who explore ChatGPT's role in academic counselling, finding that while it provides comprehensive responses to general career-related queries, it lacks precision in institution-specific advice. Similarly, Bilquise, Ibrahim & Salhieh (2024) investigate the factors influencing students' acceptance of academic advising chatbots, finding that perceived ease of use and social influence significantly impact adoption, while trust and perceived usefulness are less decisive. These findings suggest that while AI-powered advising systems have strong potential, they must be designed to foster trust and provide tailored, reliable information. Several studies highlight the potential of chatbots to improve learning outcomes. Essel et al. (2022), through a quasi-experimental pretest-posttest study, show that students who engaged with a virtual teaching assistant chatbot performed better than those who relied solely on instructors. Roca et al. (2024) further demonstrate that chatbot-assisted learning increases student motivation, satisfaction, and engagement, findings that support Sweidan et al. (2021), who show that an Android-based bilingual chatbot significantly improved student access to academic resources during the COVID-19 pandemic. This growing body of evidence confirms that chatbots play a crucial role in creating interactive and supportive learning environments.

Beyond learning, chatbots have also been utilised for administrative and support services. Hien et al. (2018) develop FIT-EBot, an AI-powered chatbot that automates responses to common student queries, reducing the workload for faculty and administrative staff. Likewise, Dhandayuthapani (2022) proposes a cognitive framework for a student support chatbot integrating natural language processing (NLP) for academic and administrative assistance, which aligns with Nguyen et al. (2022), who deploy AI-powered robotic assistants, including virtual assistants, telepresence, guides, and delivery robots, to enhance smart university operations. These studies underscore that AI-driven automation in higher education can significantly optimise resource allocation and staff efficiency. An additional emerging area in AI-assisted education is predictive analytics for academic counselling. Majjate et al. (2023) develop an AI-based academic guidance system that predicts students' admission chances and recommends universities based on their profiles, showcasing high predictive accuracy using machine learning techniques. Unlike traditional chatbots, this model moves beyond query-based interactions to provide data-driven academic recommendations. While effective, such AI models lack interactive and dynamic advisory functions, highlighting the

need for a hybrid approach combining predictive analytics with real-time chatbot counselling.

Despite these advancements, a critical research gap remains in the development of a comprehensive robo-advisory system for virtual universities that integrates AI-driven academic counselling, predictive analytics, and chatbot-assisted engagement. Existing studies, such as those by Akiba and Fraboni (2023) and Chun Ho et al. (2018), focus primarily on chatbots for academic queries, while Majjate et al. (2023) emphasise predictive guidance but lack interactive counselling elements. Similarly, Nguyen et al. (2022) explore AI-based robotic assistants, yet these are designed for physical campus environments rather than virtual universities. To address this gap, this study aims to develop a chatbot-driven robo-advisory system tailored for smart student counselling in virtual universities, combining AI-driven predictive insights with conversational interfaces for personalised academic and career guidance. This approach will ensure that students receive accurate, adaptive, and real-time support, bridging the divide between human and AI-powered advising.

3. Methods

3.1 Research approach and scope

This study focuses on the technical development, implementation, and evaluation of a GPT-based robo-advisory system using GPT-4o in a virtual university setting. The primary goal is to investigate how academic data — including module handbooks, examination criteria, study regulations, and administrative information — can be effectively integrated into a large language model (LLM) to provide context-aware and accurate student advisory services. The research will take a functional and technical approach, focusing on knowledge integration and the development of a GPT-based robo-advisor for effective integration in virtual universities.

3.2 Case study: International University of Applied Sciences (IU), Germany

To ensure the applicability of the proposed model, the study applies the International University of Applied Sciences (IU) in Germany as an exemplary case (IU, 2025). IU, Germany's largest university, provides an ideal testing ground due to its extensive digital learning ecosystem, diverse programme offerings in German and English, and hybrid educational models. Founded in 2000 in Bad Honnef, IU now supports over 130,000 students through flexible learning formats, including dual, distance, and hybrid education, with 38 campuses across Germany and a virtual campus. The GPT-based system integrates key academic resources mentioned in 0. The GPT-based system will allow students to access relevant academic information through a conversational AI model.

3.3 Data processing and knowledge integration

The analysis begins with the preparation and structuring of university-specific data to optimise their integration into GPT-4o. This process begins with the collection of relevant academic information, including course catalogues, examination criteria, study regulations, and administrative guidelines. These documents form the basis of the chatbot's knowledge base, ensuring that responses to student queries are based on official university policy. Once the data is collected, it undergoes a pre-processing phase to improve clarity, consistency, and accessibility. Some texts are standardised and formatted as normal text to reduce ambiguity and make them more compatible with the natural language processing capabilities of a language model. Finally, a systematic verification process ensures that no conflicting information is included, maintaining the credibility and reliability of the chatbot's responses.

3.4 Design and customisation

The design phase focuses on developing an effective framework for integrating the GPT-based advisory chatbot into the digital ecosystem of a virtual university by developing a GPT in ChatGPT, which can be used via the ChatGPT web interface through the OpenAI website. The chatbot is structured as a text-based conversational AI system that allows students to enter queries related to courses, exam requirements, or administrative processes. The system is designed to process natural language input, retrieve the most relevant information from the structured knowledge base, and generate responses that comply with official university policies. To optimise usability, the chatbot operates as a standalone model, accessible via direct text input, with the potential for future integration into university platforms. Although no front-end development is undertaken in this study, the chatbot's architecture as a GPT is designed to allow seamless API-based integration into existing university websites, mobile applications, or learning management systems.

3.5 Testing and statistical validation

Test Evaluation of system functionality will be conducted through direct interactions with the chatbot, verifying the accuracy of retrieved information, and testing its ability to handle queries. The system is then tested using 100 prompts, and the accuracy of the information is evaluated. The following accuracy metrics are used:

$$\text{Precision} = \frac{\text{Correct Responses}}{\text{Correct Responses} + \text{Incorrect Responses}} \quad (1)$$

Precision measures the proportion of correct responses among all generated responses. It indicates how well the system avoids incorrect answers.

$$\text{Recall} = \frac{\text{Correct Responses}}{\text{Correct Responses} + \text{Missed Correct Responses}} \quad (2)$$

Recall assesses the system's ability to retrieve all relevant correct answers. In this case, as all responses were correct, recall is maximised.

$$\text{F1 Score} = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \quad (3)$$

The F1-score is the harmonic mean of precision and recall, providing a balanced metric when both are equally important.

$$\text{Overall Accuracy} = \frac{\text{Correct Responses}}{\text{Total Responses}} \quad (4)$$

Overall accuracy represents the proportion of all correctly answered queries relative to total queries tested.

4. Results

4.1 Requirements

The functional requirements in Table 1 define the expected capabilities of the GPT-powered advisory system to provide accurate, structured, and context-aware responses to student enquiries.

Table 1. Functional requirements of the GPT-powered advisor for student counselling

Requirement	Description
Contextualised Responses	The system should provide responses based on specific university documents, such as module handbooks, examination regulations, and administrative policies. Each response should reference the relevant section for further verification.
Short, Focused Answers	Responses should be concise and to the point, only providing essential information. If a topic requires further clarification, students should be encouraged to ask follow-up questions.
Accuracy and Source Linking	The chatbot should ensure that all responses are factually accurate and include references to the original sources, e.g., "See Module Handbook, Section 3.2 for details on course prerequisites."
Adaptive Query Handling	The system should be able to disaggregate complex questions into smaller, manageable parts and provide step-by-step guidance when required.

Multilingual Support	It should support responses in German and English, allowing students to select their preferred language.
Clarification Prompts	At the end of each response, the chatbot should ask: "Would you like me to cover any further aspects related to your question?"
Categorised Information Retrieval	Student enquiries should be categorised into course-related, examination-related, or administrative topics to provide more structured responses.
Handling of Unclear Queries	If a student's question is ambiguous, the chatbot should respond with: "Could you clarify your question? For example, are you asking about course selection, exams, or administrative procedures?"
Guidance on Next Steps	When providing answers, the system should suggest possible next steps for students, such as contacting specific departments if additional verification is needed.

The technical requirements in Table 2 define how the system handles requests, retrieves data, and ensures a seamless user experience.

Table 2. Technical requirements of the GPT-powered advisor for student counselling

Requirement	**Description**
Integration with Knowledge Base	The chatbot should access structured university data (module handbooks, exam policies, and study regulations) through retrieval-augmented generation (RAG) techniques to improve response accuracy.
Natural Language Understanding (NLU)	The GPT model should support semantic understanding of student queries, allowing for flexible phrasing without relying on exact wording.
Data Preprocessing & Structuring	University documents should be preprocessed into structured formats (e.g., categorised text snippets) for efficient retrieval.
Information Retrieval Mechanism	The chatbot should retrieve answers based on keyword matching, semantic search, and contextual ranking to ensure relevant responses.
Query Logging & Optimisation	The system should track commonly asked questions to refine response quality over time, ensuring frequent enquiries are answered efficiently.
Privacy & Data Security	No personal student data should be stored or processed. The chatbot should comply with General Data Protection Regulation (GDPR) and university data protection policies.
API-Based Deployment	The model should be accessible via an API, allowing for future integration with university platforms, including websites and mobile applications.
Scalability &	The system should be optimised for handling high query

Load Management	volumes simultaneously to support a large number of students efficiently.
Fail-Safe for Unanswerable Questions	If a query cannot be answered, the chatbot should respond with: "I currently do not have this information. Please check [University Portal] or contact the administration."
Update Mechanism	The chatbot should allow for regular updates to ensure information remains accurate when university regulations change.

4.2 Implementation for study programmes

Table 3 shows the degree programmes considered in the development of the GPT robo-advisory system for student counselling. In total, the module handbooks of 29 textbooks were considered. In addition, various general regulations, FAQs and examination criteria from the university were included. Since the module handbooks each comprise over 600 PDF pages, they were split into different sub-GPTs during implementation to make it easier for the limited computing capacity of GPT-4o to process the sheer volume of data. In more advanced GPT models, which can handle significantly more computing capacity and input data, all documents can also be linked to a single GPT if required.

Table 3. Degree programmes considered in the development of the GPT-powered advisor for student counselling

Study Type	**Programmes**	**Quantity**
Bachelor	Applied Artificial Intelligence, BSc in Cyber Security, Industrial Engineering & Management, Computer Science, Business & IT, International Management, Business Administration	7
MBA	Human Resource Management, Healthcare Management, Artificial Intelligence, Master of Business Administration, IT Management, International Marketing, One-year MBA, Engineering Management, Big Data Management, Innovation & Entrepreneurship, E-Sports Management, Finance & Accounting, Supply Chain Management	13
Master	Engineering Management, Computer Science, Artificial Intelligence, International Management, Cyber Security, International Management, Management + Majors, Data Science, Data Science	9

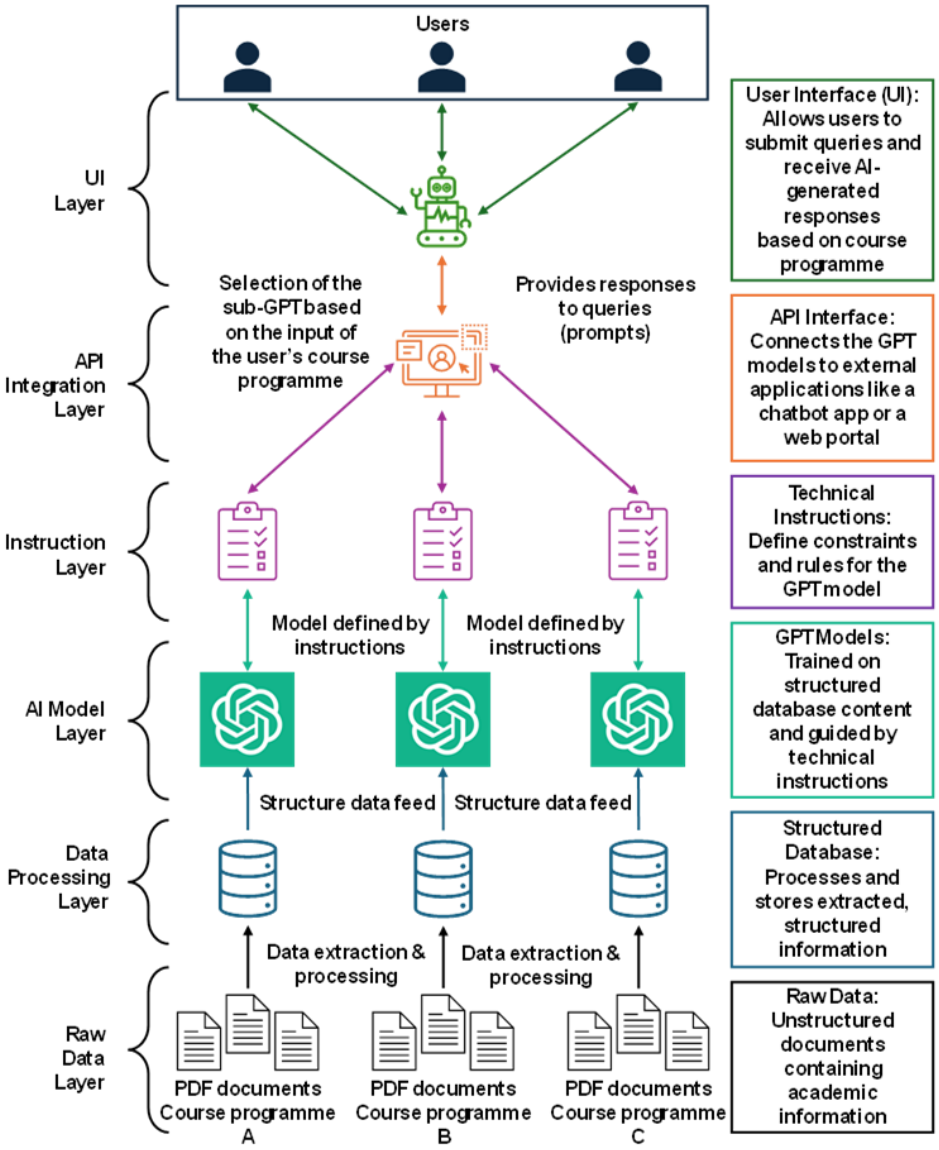

Figure 1. Illustration of the architecture diagram with the workflows, objects, and layers for the robo-advisory system for smart student counselling

Figure 1 shows a conceptual architecture diagram with the workflows, objects and layers for the robo-advisory system for smart student counselling, as it could be implemented in practice. The user interface (UI) or application programming interface (API) should already identify the course programme for which questions are to be asked by the user, based on the profile entered, e.g., matriculation or personnel number, name, or course programme. After

clarification, the upper layers can select the appropriate GPT defined by the instructions and send the queries to forward, process, and return the answers to the user. This process is a simplified illustration and suggests future generative AI models with significantly more computing power and input sizes (tokens) can later be consolidated into a "SuperGPT" that contains all study programmes and all documents in a single big database.

Each university can specify its own suitable structure with a selection of documents based on the information it wants to input into the robo-advisor. The documents should also be updated when changes are made, e.g., when the module content or requirements change, so that the robo-advisor is always up to date. Versioning could even help to explain the old and new study regulations to students when changes are made, thus helping to ensure traceability and transparency when changes are made. However, this was not considered for this study due to the complexity of implementation. Essentially, a large part of the work for the implementation lies in the raw data layer and data processing layer for preparing and structuring the data basis, as well as in the instruction layer for customising the robo-advisor. The core is already defined by the AI model. All layers after that refer to the API and UI and can be implemented in a customised manner depending on the application, e.g., desktop, mobile application, or student portal.

4.3 Test results and evaluation

The system was tested using 100 sample prompts developed by students to assess its accuracy. The prompts covered a variety of categories, including academic programmes, examination regulations, careers advice, and administrative processes. Table 4 displays several examples with test results for each category.

Table 4. Example prompt and result of the 100 prompts by category

Category	Example Prompt	Example Answer
Degree Program Information	What are the core subjects in the Bachelor's program-me in Applied AI?	The core subjects include Machine Learning, Neural Networks, Data Analytics, and Ethics in AI.
Examination Regulations	How many attempts do I have for a failed exam?	According to university regulations, students are allowed three attempts before needing to apply for an exception.
Career Guidance	Which industries can I work in after completing a Master's in Data Science?	Graduates can work in finance, healthcare, technology, and academia as data analysts, machine learning engineers, and AI specialists.

Administrative Procedures	How can I apply for a leave of absence?	Students must submit a request form through the student portal and provide a valid reason, such as medical or personal circumstances.
Course Content & Module Handbooks	What topics are covered in the Cyber Security Master's programme?	The program covers Network Security, Cryptography, Ethical Hacking, and Security Management.
General University Policies	What is the plagiarism policy at the university?	The university follows a strict plagiarism policy. Any detected plagiarism results in disciplinary action, including possible course failure.
Student Life & Campus Resources	Are there any student support services available?	Yes, the university offers counselling, career services, and academic tutoring for students.

The statistical test results of the queries per category are shown in Table 5 and show an accuracy of 100%. Accordingly, no incorrect or missing information was retrieved, and all questions could be answered correctly.

Table 5. Statistical test results of the queries per category

Category	**Queries (Prompts)**	**Precision (1)**	**Recall (2)**	**F1-score (3)**	**Overall Accuracy (4)**
Degree Programme Information	30	100%	100%	100%	100%
Examination Regulations	15	100%	100%	100%	100%
Career Guidance	10	100%	100%	100%	100%
Administrative Procedures	10	100%	100%	100%	100%
Course Content & Module Handbooks	15	100%	100%	100%	100%
General University Policies	10	100%	100%	100%	100%
Student Life & Campus Resources	10	100%	100%	100%	100%

5. Discussion

The implementation of the GPT-powered robo-advisor system for student counselling demonstrated remarkable accuracy and efficiency. The system was tested using 100 sample prompts covering various categories such as course

information, examination regulations, career guidance, administrative processes, and student support services. The results show that the system provided 100% overall accurate information, ensuring that no misinformation was given. The key success factor of the GPT-powered system is its ability to handle complex queries with contextual accuracy. Unlike traditional chatbots, which rely on pre-defined rules and structured interactions, this system uses NLP and deep learning algorithms to generate responses based on extensive academic module manuals and university regulations. Incorporating the documents into its knowledge base further contributed to the system's high accuracy in responding to student queries. In particular, the modular approach to breaking down these large documents into smaller sub-GPTs ensured efficient processing and retrieval of relevant information, thereby overcoming some computational limitations. In addition, the test results suggest that the system effectively supports personalised student advice by providing responses tailored to different study programmes and regulations. It accurately retrieved details of core subjects, exam attempts, and career paths, demonstrating its potential as an alternative to traditional student guidance.

The results are consistent with findings from the existing literature on AI-based student guidance systems. Dibitonto et al. (2018) emphasise that virtual assistants should improve accessibility and user engagement – an outcome observed in the current study, where students received immediate and reliable responses. Similarly, Martinez-Requejo et al. (2024) found that chatbots improve student engagement and administrative efficiency, a claim supported by the observed effectiveness of the GPT robo-advisory system in handling student queries about academic policies, administrative processes, and career guidance. From an academic advising perspective, the findings are consistent with those of Chun Ho et al. (2018), who developed EASElective, a chatbot that assists students in selecting electives. The ability of the GPT robo-advising system to provide detailed course descriptions and degree structures reflects similar benefits. However, a limitation highlighted by Akiba and Fraboni (2023) is that ChatGPT often lacks precision in institution-specific advice. In contrast, the GPT robo-advice system tested in this study was specifically trained on institutional policies, allowing it to overcome this common limitation. Another important finding in chatbot-assisted learning comes from Essel et al. (2022) and Roca et al. (2024), who showed that chatbots improve student motivation and learning outcomes. The GPT system's ability to generate clear, structured, and informative responses suggests that it could be extended as a learning companion beyond its use in student support. A key difference between the GPT robo-advisory system and traditional rule-based chatbots, such as those discussed by Hien et al. (2018) and Dhandayuthapani (2022), is its ability to interpret natural language variations. Unlike traditional chatbots that rely on predefined response templates, the GPT system adapts to varying phrasing, student preferences, and complex queries, providing a much more dynamic and flexible interaction model. In addition, Majjate et al. (2023) introduced predictive analytics for academic guidance, but their model lacks real-time advisory capabilities. The GPT robo-advisory system

bridges this gap by providing both interactive responses and accurate data retrieval, ensuring immediate and accurate responses rather than static, prediction-based recommendations.

Despite its effectiveness, there are several areas where GPT's robo-advisory system could be further improved. One key improvement would be the integration of predictive analytics, allowing the system to make course recommendations based on student performance trends. This would provide a more proactive and personalised advising experience that would more effectively guide students through their academic journey. In addition, while the system currently operates efficiently in English, expanding its multilingual capabilities would significantly improve accessibility for a wider range of students. Sweidan et al. (2021) have demonstrated that bilingual chatbots can improve access to academic resources, particularly in diverse learning environments. Another important consideration is the ethical dimension of AI-based advice. Chen et al. (2023) warn against over-reliance on AI for academic advising, as automated systems lack the emotional intelligence and ethical judgement required for sensitive issues such as mental health concerns or academic appeals.

While the implemented GPT robo-advisory system ensured factual overall accuracy, it cannot fully replace human advisors in complex, emotionally nuanced situations. Addressing these challenges through predictive insights, multilingual customisation, and ethical safeguards will further refine the system's effectiveness and reliability in academic counselling. Moreover, potential biases in AI-generated responses must be considered. Since language models rely on training data, biases can emerge if the data is not representative. To mitigate this, continuous refinement through diverse datasets and bias-detection mechanisms is necessary to ensure fair and unbiased academic advising. Additionally, computational limitations remain a challenge for widespread implementation. Although the system effectively handled extensive module handbooks by dividing them into sub-GPTs, further optimisation is needed for scalability. Strategies such as enhanced compression algorithms, distributed computing, or cloud-based architectures could improve efficiency without compromising accuracy. Addressing these challenges will improve the adaptability of the system, ensuring reliable and equitable access to student counselling services while maintaining high performance standards.

6. Conclusion

The results confirm that GPT's robo-advice system significantly improves the efficiency, accuracy, and accessibility of student advice services. The system successfully eliminates misinformation while handling institution-specific queries – an improvement over generic AI chatbots. Compared to traditional advising methods, the system provides immediate, data-driven insights, reducing faculty workload and increasing student engagement. While there are some limitations, the integration of predictive analytics, multilingual support, and ethical safeguards can

further improve its effectiveness. In addition, addressing potential biases in AI-generated responses through continuous refinement and diverse training data will be essential to ensure fairness and reliability in student advising. Furthermore, optimising computational efficiency through advanced processing strategies will improve scalability and enable wider institutional implementation. These findings contribute to the growing literature on AI in higher education and support the wider adoption of robo-advisors for student counselling and academic support.

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