Enhancing Information Technology Governance in Universities: A Smart Chatbot System based on Information Technology Infrastructure Library

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ABSTRACT

The rapid evolution of information and communication technologies has created a pressing need for higher education institutions to modernize their Information Technology (IT) governance practices. This article proposes an innovative solution to enhance the governance and efficiency of IT services while optimizing and personalizing user experience. The proposed solution consists of a chatbot using Artificial Intelligence (AI) and Natural Language Processing (NLP) combined with the Information Technology Infrastructure Library (ITIL) standard to automate the management of IT services in the digital work environment (ENT). Intended for students, teachers, and administrators, this chatbot provides reactive support by responding to requests, reducing waiting times, and improving satisfaction. It also helps decrease operational costs and the workload of support teams by autonomously handling recurring requests. Beyond efficiency improvements, the chatbot contributes significantly to IT governance by providing structured service management, improving decision-making through real-time data, and supporting compliance with governance frameworks. An online survey conducted among 120 students revealed slow processing of requests and unavailability of services, justifying the need for this chatbot. The chatbot was designed with advanced NLP and Machine Learning (ML) technologies. Preliminary tests demonstrate the chatbot's response reliability, with an accuracy rate of 96% and a response time decrease to an average of 4.17 seconds. The use of chatbots has considerable potential for universities to improve the efficiency of digital services offered to students.

Keywords-artificial intelligence; machine learning; ITIL; chatbot; university; NLP; LLM

I. INTRODUCTION

Digital services have become necessary for the functioning of modern universities, facilitating course management, digital library access and administrative services. However, the diversity and complexity of information, combined with the lack of personalized and immediate support, present major challenges for students and teachers [1]. Traditional solutions, such as FAQs or online forums, are no longer sufficient, while human support is limited by budgetary and staffing constraints. This issue highlights the need for universities to rethink their digital strategies in order to improve service accessibility and operational efficiency. In this context, AI and particularly chatbots based on NLP, offer an innovative solution for improving educational services [2] and provide automated, instant, and personalized support [3]. However, the design of chatbots specifically intended to interact with users in an intuitive manner, providing accurate and rapid responses to their questions remains a relatively unexplored area. The present study aims to fill this gap by proposing the design and development of a chatbot attempting to improve the governance of university information systems. The adopted methodology is based on the integration of the ITIL framework in combination with AI technologies to automatically manage service requests.

It is a fact that ITIL offers a structured set of processes and practices enabling organizations to deliver IT services more efficiently by standardizing procedures and improving communication between teams [4]. The ITIL version 3, published in 2007, introduced the concept of a service lifecycle structured into five phases [5]. This approach enabled effective management by aligning IT services with business needs and focusing on process management and documentation. According to [6], the application of ITIL in universities has optimized IT service management processes, thereby enhancing the quality and responsiveness of services offered to students and staff. Case studies show that adopting ITIL helps these institutions adjust their IT services to the specific users needs and manage incidents, problems, and changes more effectively. In addition, authors in [7] pointed out that the ITIL framework offers a structured approach facilitating better coordination between departments and enabling proactive service management. However, as stated in [8], implementing ITIL in higher education presents certain challenges, such as the resistance to change, complexity of integration, and difficulty of full deployment. It is therefore necessary to for ITIL to be adapted to the university context, where the scope covered by the IT department is vast and extensive, and the practices used are heterogeneous.

AI has become a key research topic in science and technology sectors, attracting the interest of major companies who are striving to integrate it into numerous fields [9]. Its applications are vast and varied, ranging from recommendation systems to voice recognition. In 2016, AlphaGo captured worldwide attention by beating the world chess champion, illustrating AI's advanced capabilities [10]. In education, AI can be utilized to personalize students' educational pathways by creating adaptive learning platforms and automating the assessment process. ML algorithms enable universities to optimize the use of their resources, including infrastructure and staff, as well as to automate schedule and timetable management taking into account student preferences and teacher constraints in an attempt to create optimal schedules, and forecast course enrollments. This helps them adjust classroom and teacher allocation, accordingly, and reduce inefficiencies and costs [11]. ML algorithms suggest personalized courses and extracurricular activities based on students interests and past performances. They can also analyze past interactions with the platform to propose content and services tailored to their specific needs, recommending additional courses or further readings on frequently accessed topics [12]. Generative AI focuses on creating new content from existing data. Generative AI models, such as Generative Adversarial Networks (GANs) [13], are used to generate images, texts, and even videos, offering significant possibilities in various sectors, namely arts, advertising, design, educational applications, where creativity and rapid content production are essential. Authors in [14, 15] demonstrate the crucial role of generative AI models in anomaly detection and fraud prevention, as well as in other fields such as medicine [16] and retail [17]. In the education sector, these models are employed to create personalized educational content, interactive quizzes, and course materials tailored to the individual needs of students. Generative AI can enrich user experience by providing dynamic and contextually appropriate responses [18]. More recent research has focused on improving chatbot capabilities utilizing sequential models, such as Recurrent Neural Networks (RNNs), Deep Neural Networks (DNNs), and Convolutional Neural Networks (CNNs). For example, authors in [19] proposed DeepProbe, an RNN-based information driven understanding and chatbot design system. A study carried out in [20] examined interdisciplinary learning principles in a different domain, where the chatbot's contextual understanding is enhanced through dynamic knowledge graphs that capture users' past interactions to provide up-to-date and relevant answers. By integrating explainability features, chatbot responses are enriched, enabling users to understand the reasoning behind the answers.

The main contributions of this study lie in the creation of a knowledge base specifically adapter to the university and the development of a chatbot capable of interacting with users by exploiting this knowledge base.

II. METHOD

A. Data Collection

To ensure the relevance and effectiveness of the developed chatbot, an online survey with 120 students, mainly engineering ones, was conducted to gather their specific needs and expectations regarding university digital services. The results of this survey revealed recurring issues, such as slow processing of requests and the unavailability of services, justifying the need for an automated and personalized support. Figure 1 illustrates the various problems encountered by the students.

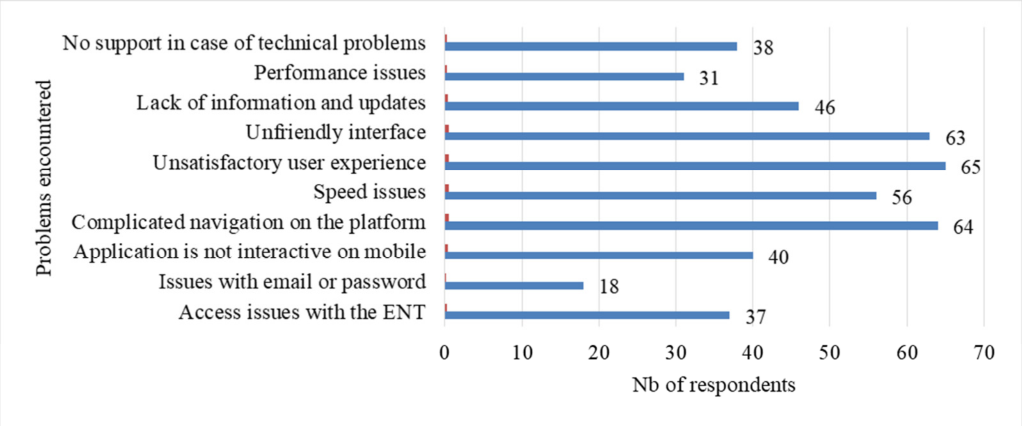

Fig. 1. Problems faced when using ENT.

In addition to the information gathered throughought the survey, a series of PDF files containing all relevant information related to the services available on the ENT and university platforms was collected. These services include registration procedures, email management, access to courses and educational resources, academic results, timetables, online training, news, and announcements. The data contained in these PDFs will be used to respond to users' questions and needs.

Gathering student feedback was crucial in adapting the proposed solution to an efficient application capable of interacting with users by leveraging PDF documents, taking under consideration essential documentation formats since 1995. LLMs capabilities, such as ChatGPT, Bing AI, and Bard AI were also leveraged.

B. Chatbot Design and Architecture

This phase corresponds to the Service Design phase of the service lifecycle. It involves identifying the chatbot's various use cases, defining its architecture, developing use scenarios for user-chatbot interactions, and designing an intuitive user interface accessible to all users. The architecture of the proposed chatbot is based on the Retrieval-Augmented Generation (RAG) model, which combines retrieval and generation approaches to provide more accurate and contextually relevant interactions. This innovative model incorporates several key elements, including chunks, embeddings, and vectors, to enhance the efficiency and accuracy of the responses. Figure 2 presents the overall architecture of the proposed system.

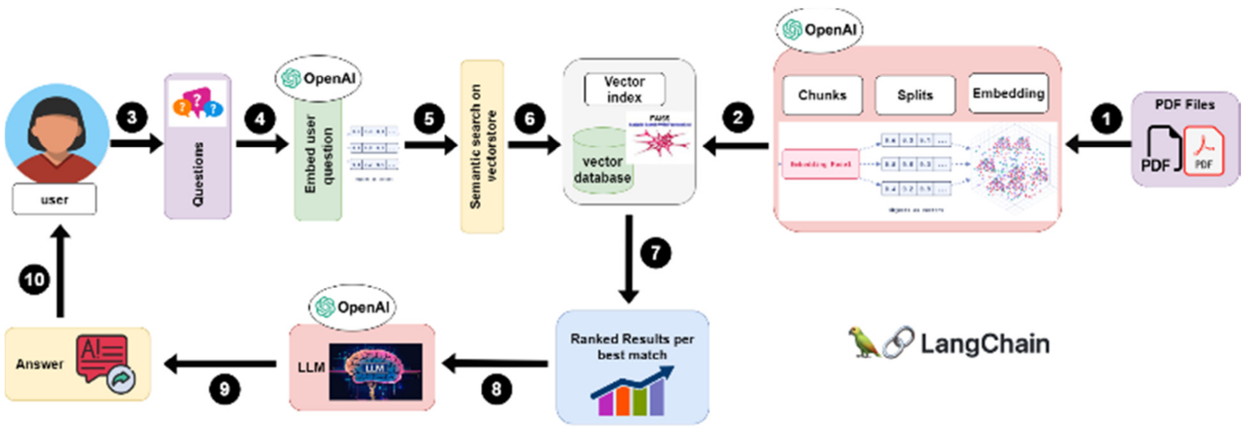

Fig. 2. Chatbot architecture.

PDF documents are first loaded and their content is extracted. The content is then segmented into chunks, subsequently converted into numerical vectors called embeddings, which capture the semantic meanings of words or phrases. These embeddings, which are obtained using GPT's pre-trained language models and are deployed to represent the similarities and differences between linguistic concepts mathematically, are stored in a vector database that was implemented utilizing FAISS. The user's question is also broken down into chunks, which are then converted into embeddings that the system uses to query the database. The system analyzes the query to extract its meaning and structure and then compares it to the vectors of the document chunks to find the most relevant responses to return to the user. This step is performed employing cosine similarity techniques, enabling the chatbot to retrieve the most relevant information based on the context provided by the user. The ChatOpenAI along with the GPT-4-o model and LangChain were put into service to manage the user queries and data flow between the different stages, ensuring a smooth integration and an efficient management of text and queries. To allow users to interact with the chatbot, a Streamlit-based user interface was developed utilizing Python. Streamlit stands out for its ease of use and speed compared to other tools.

C. Tools and Technology

The selection of tools relevant to the proposed solution was made following a comparison between the most widely deployed models and databases. Table I presents a comparison between Meta's Llama 2 model [21] and OpenAI's GPT-4 model in terms of features, performance, and access, while Table II summarizes the comparison of the databases.

TABLE I. COMPARISON BETWEEN LLMS

Criteria	OpenAI's GPT-4	Meta's Llama 2 [21]
Size	1.76 trillion parameters	7 to 70 billion parameters
Nature	Proprietary	Open-source
Architecture	Multimodal (text and image)	Unimodal (text)
Performance	Outperforms Llama 2 in natural language understanding, programming, mathematical reasoning	Less effective in complex tasks
Multilingual Support	Excellent multilingual coverage	Limited
Accessibility	Accessible via official API, fine-tuning options	Local download and execution

TABLE II. COMPARISON BETWEEN VECTOR DATABASES

Criteria	FAISS	Chromadb, Pinecone
Optimization	Optimized for dense similarity search	Less optimized for dense similarity
Techniques Used	Quantization, partitioning	Techniques vary depending on the database
Performance	High performance for large datasets	Variable performance
Advantages	Semantic relevance, operationalization of embedding models, AI performance improvement	Varied capabilities depending on the database

GPT-4 was chosen due to its superior performance in NLP understanding, reasoning, and multilingual capabilities compared to other models like LLaMA 2. GPT-4 was consistently outperformed in terms of complex query handling and understanding nuanced user intents, which was crucial for this study's chatbot use case in a diverse university setting. FAISS was selected as the vector database due to its high performance in dense similarity searches, which is essential when dealing with large datasets and semantic searches, such as those performed by the proposed chatbot. Its quantization and partitioning techniques allow it to operate efficiently even with extensive data, which was a priority for ensuring the scalability and robustness of the system.

III. TESTING AND VALIDATION

This test and validation section is a part of the Service Transition phase in ITIL, aiming to deploy IT services and verify that changes to service management processes are carried out in a safe and coordinated way. The purpose is to test the chatbot's performance and reliability in different scenarios to ascertain that it works properly and meets student needs. To test the proposed chatbot, a representative set of 24 questions was designed based on the needs and concerns expressed by ENT users collected through the survey. These included questions about navigating the platform and resolving technical issues. The expected answers were then designed before querying the chatbot, while the responses provided, as well as the response time per question were recorded. A true/false test was used to evaluate the accuracy of the answers, noting whether they were correct (true) or incorrect (false). When the chatbot encounters queries that extend beyond its existing knowledge base, it utilizes fallback mechanisms to either clarify the user's request or direct the user to human support. Figure 3 illustrates an interaction between the chatbot and a user. To calculate accuracy, this study determined the percentage of correct responses relative to the total number of questions asked. It also deployed a confusion matrix to visualize the bot's performance in terms of classifying correct and incorrect answers. Response time analysis was used to assess the bot's speed in providing answers. The confusion matrix evidenced in Figure 4, indicates that there was only one instance where the chatbot failed to correctly answer a question that should have been correct, but there were no false positives, which means that no incorrect responses were identified as correct.

The results of the chatbot evaluation exhibit an overall satisfactory performance. The accuracy is 0.96 and additional performance metrics, such as precision, recall, and the F1-score, were calculated to obtain a more comprehensive assessment of the bot's reliability. Precision is 1.00 and recall is 0.96. The F1-score, a measure combining precision and recall, is 0.98, underlining a very good balance between the two metrics. The graph depicted in Figure 5 reveals that the majority of responses are provided within 2 to 6 seconds, with some variations being faster or slower. The average response time of the chatbot is 4.17 seconds, which is fast enough to guarantee a smooth and efficient user experience. These results demonstrate that the chatbot is well-optimized to respond to students' queries while offering an intuitive interface and a satisfying user experience.

IV. DISCUSSION

The deployment of the chatbot in the university environment illustrates a practical application of the ITIL processes, specifically tailored to improve service request management. The introduced chatbot effectively addresses common issues encountered by university students, identified through the preliminary survey. The discussion carried out in [20] regarding the best practices and case studies demonstrates how ITIL improves the efficiency of IT operations and user satisfaction by providing structured processes for incident, problem, and service request management. Integrating feedback loops and incident reports into the chatbot's functionalities can significantly reduce response times and improve user satisfaction. This study's findings confirm these observations, showing that the chatbot has significantly reduced the response time to frequently asked user questions.

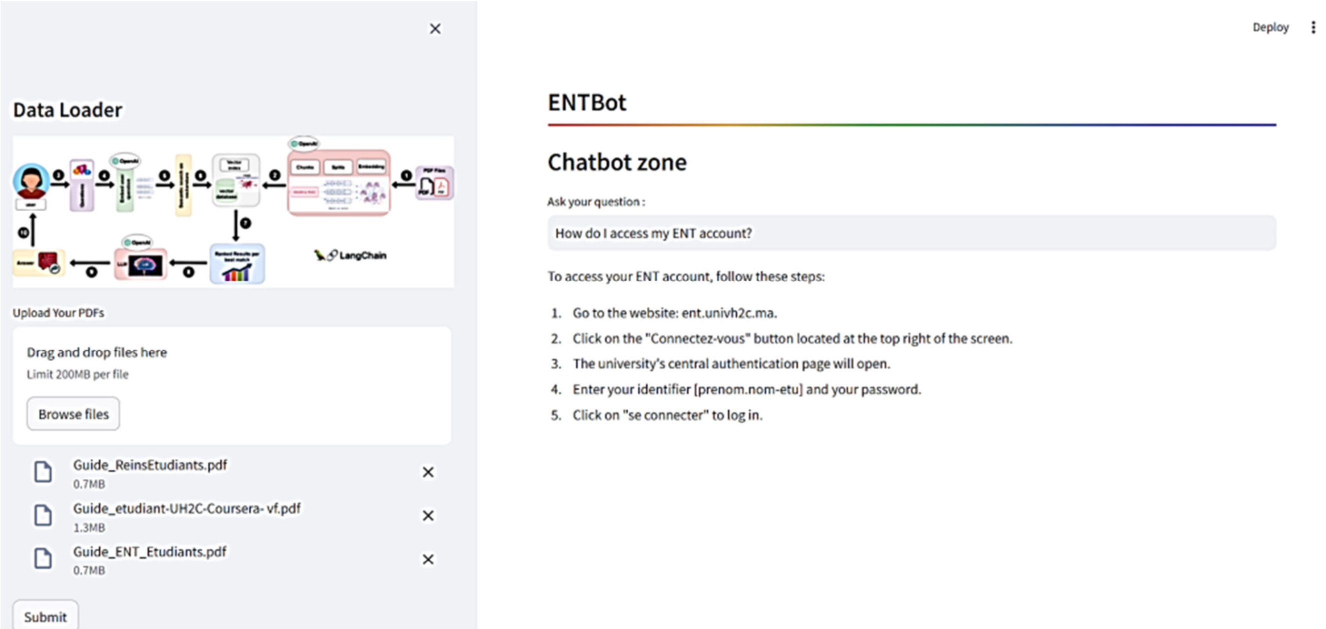

Fig. 3. Interaction between the chatbot and a user.

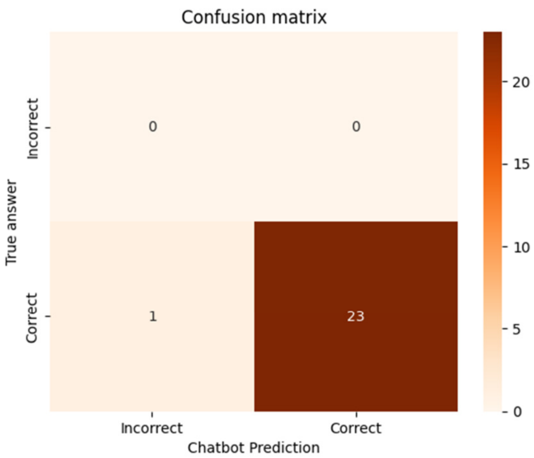

Fig. 4. The confusion matrix.

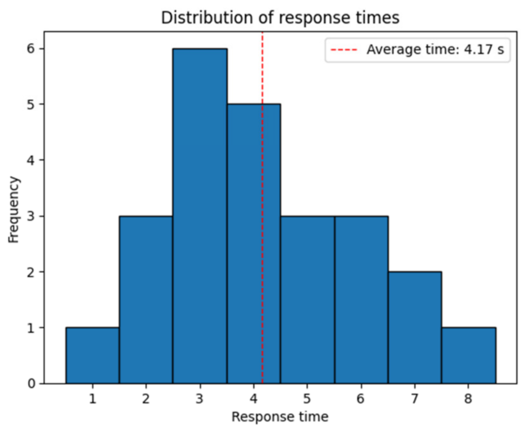

Fig. 5. Response time.

The combination of ITIL and AI is opening up new opportunities for Moroccan universities in terms of information system governance. By optimizing operational efficiency, strengthening system resilience, and improving service quality, this innovative approach can help propel higher education institutions towards technological excellence while meeting the evolving needs of the academic community [1]. The proposed chatbot represents an approach covering a wide range of academic and administrative services. It is distinguished by its integration with an extensive knowledge base specific to the Moroccan university. This enables it to respond in a more contextualized and relevant way to the needs of students and academic staff. Additionally, the chatbot's 24/7 availability certifies that students have access to the assistance they need, a critical aspect highlighted in [23]. However, advanced ML and predictive analytics technologies could be explored to further enhance the former's effectiveness.

The results of the chatbot evaluation suggest an overall satisfactory performance, with high-quality responses. In comparison to the chatbot systems, like those implemented along with IBM Watson or ServiceNow, which have achieved similar performance levels, the proposed solution stands out due to its specific adaptation to the needs of Moroccan universities. Additionally, the integration of ITIL processes enhances the structure and efficiency of the chatbot, which may not be the case in more general implementations. Though, despite the promising results, several challenges remain. The sample of 120 students, while representative, may not reflect the full range of needs across the entire university population. A broader survey, including students from other disciplines, levels, institutions, or nationalities, would help gather more diversified data and adjust the chatbot accordingly. Furthermore, the chatbot's performance is directly linked to the quality and quantity of data available in the knowledge base. As new documents and information are added, it will be necessary to regularly update this knowledge base to maintain the relevance of the responses. Integrating continuous ML capabilities could also help the chatbot get autonomously improved over time.

V. CONCLUSION

This study examined the integration of AI-powered chatbots with ITIL standards to enhance the governance and efficiency of information systems in Moroccan universities. It demonstrates that chatbots, using advanced Natural Language Processing (NLP) and Machine Learning (ML) technologies, can greatly ameliorate student, faculty, and administrative staff experience. By providing accurate and prompt responses, these chatbots reduce waiting times, increase satisfaction, and lighten the workload of IT support teams by autonomously handling repetitive requests. The current study contributes to the growing body of literature on AI employment in education, offering empirical evidence of the benefits and challenges of deploying chatbots, as well as insights into their potential to revolutionize student support services. The continuous improvement of these systems, supported by ITIL principles, will be essential for meeting the evolving needs of students and educational institutions, hence enhancing the governance of university information systems.

Future research should focus on two key areas: Initially, on the deployment of the chatbot within the university's digital learning environment using the most appropriate infrastructure that addresses to data security and privacy standards to ensure scalability and reliability, and second, on the continuous improvement of the system based on previous interactions and user feedback analysis, which will help fine-tune the search and generation algorithms to ascertain an ongoing adaptation to user changing needs and the application domain.

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