# AI-based Academic Advising Framework: A Knowledge Management Perspective

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***Abstract*—Academic advising has become a critical factor of students' success as universities offer a variety of programs and courses in their curriculum. It is a student-centered initiative that fosters a student's involvement with the institution by supporting students in their academic progression and career goals. Managing the knowledge involved in the advising process is crucial to ensure that the knowledge is available to those who need it and that it is used effectively to make good advising decisions that impact student persistence and success. The use of AI-based tools strengthens the advising process by reducing the workload of advisors and providing better decision support tools to improve the advising practice. This study explores the challenges associated with the current advising system from a knowledge management perspective and proposes an integrated AI-based framework to tackle the main advising tasks.**

***Keywords*—Knowledge management; artificial intelligence; academic advising; rule-based expert system; machine learning; chatbot; conversational agent***

## I. Introduction

Student retention and persistence are the most critical objectives of Higher Education Institutions (HEIs) as they are striving to meet the demands of the global economy. Graduating students on time is not just a measure of student and institutional success but also has a positive impact on the economy and society at large. In the United States, one out of three students does not progress from freshman to sophomore year, while in Australia nearly 30% of students do not graduate with a degree [1]. In UAE the rates are similar, with nearly 25-30% of students dropping out from a degree program [2]–[4]. With the astounding rate of university dropouts worldwide, academic institutions are striving hard to develop initiatives that mitigate the early leavers and provide the necessary support to students for on-time graduation [2].

Academic advising has been widely accepted as a vital strategy to tackle the problem of persistence and retention [5]–[7]. Advising is an essential process in academic institutions for engaging, supporting, and guiding students throughout their academic tenure. Tinto's prominent study [8] on the theoretical framework of retention states that students' engagement within the institution has a direct impact on reduced attrition rates. A broad definition of academic advising is provided by [9], who state that advising is the process ensuring student success through various interactions and between a student and members of the academic institution. Although there are several facets of academic advising, the main objective of advising is to effectively manage a student's journey to ensure academic success.

The process of advising encompasses several tasks such as ensuring students are informed about the institutional policies, courses, and program requirements and that they enroll for courses according to their degree plan. Furthermore, advising ascertains that students follow a customized learning track based on their academic progression [10]. Academic advising also offers extra support and guidance to students who need it the most [6], such as the students on probation or at risk of dropping out or failing a course.

Knowledge management (KM) is an integral part of academic advising. The process of advising involves the use of tacit and explicit knowledge to guide and support students throughout their academic life. Academic advisors assist students in various tasks such as selecting ideal courses, supporting at-risk students, providing necessary information that is vital to the student's successful integration with college life. Moreover, academic advisors also utilize their knowledge in solving issues that students face in achieving their academic goals. At the institutional level, the knowledge of the advisors must be captured, stored, and shared to ease the process of advising for new advisors as well as to retain knowledge within the institution. To this effect, technology provides an efficient means of disseminating knowledge among institutional members.

In the current age of digital transformation, Artificial Intelligence (AI) offers a promising avenue to effectively support the advisory process by providing benefits that are otherwise not attainable using a traditional advisory system. AI-based systems can automate the task of identifying students at risk, recommending courses, and answering student queries. These systems have the potential to not only reduce the workload of advisors but also enhance the services provided to students and support their academic progression [10]. Although there is a vast amount of research on supporting students using AI, there is no study that has investigated a comprehensive AI solution that tackles all the challenges of the traditional advising process.

The purpose of this study is to investigate the limitations of academic advising under the lens of KM and propose an AI-based solution for an academic institution based in the UAE. The study explores the problems of the advising system currently in place and offers a holistic solution based on AI technologies that integrate with the current information system. The key requirements of the proposed solution are discussed with an implementation strategy.

The rest of the paper is organized as follows. Section II presents the background information of the higher education institution of this study and the advising process thereof. Section III highlights the problems of advising at the institution of study. Section IV reviews AI-based advising solutions in the existing literature. Section V discusses the proposed AI-based solution for the HEI of this study, and finally, the paper ends with a conclusion that provides a summary of the paper, limitations of the study, and further research avenues.

## II. Background Information

The process of advising and the roles of the institutional members involved thereof may differ from one academic institution to another. This section describes the advising process followed at the institution of study and explains the roles of the academic advisor.

The academic institution of this study is one the largest higher education institution in the middle-east region. The institution offers six undergraduate programs of study and has an intake of nearly 500 students each term. After enrollment, students are provided credentials to access online resources such as the portal, emails, and the learning management system. Orientation sessions are held for the new students and an academic advisor is assigned.

Academic advising, at the institution of study, is a role assigned to every faculty member. Each faculty is assigned 25-30 advisees, who are students enrolled in the same program. The advising tasks and the advising process are consistent across all the programs. Therefore, this paper does not focus on any particular program of study, but rather the advising process as a whole.

An advisor's role encompasses three main tasks – creating a customized study plan for academic progression, providing guidance and support to answer queries and recommend opportunities for personal and career growth, and finally, monitoring academic progression and supporting students at risk.

First, an advisor liaises with each advisee to create a study plan by recommending courses every semester. A good study plan ensures a smooth academic progression in the program of study. The advisor must select appropriate courses that best meet the academic requirements such as pre-requisites, minimum credits, specialization, and more. The advisor also prepares a graduation plan during the final year of an advisees study to ensure on-time graduation.

The second advisory task is to offer guidance for general academic queries. The advisor is the central contact point for advisees who need direction and support for any personal or academic. An advisor directs the student to support systems provided by the institution such as student services, academic tutorials, or answers their general queries about grades, volunteering hours, GPA requirements, work placement, and more. This type of advising strengthens the student's bond with the institution as they feel connected to their environment. The advisor also corresponds with the advisees to encourage them to participate in extracurricular opportunities, competitions, and programs related to their career and personal growth. Moreover, advisees often reach out to their advisors for general guidelines and information on policies and procedures. The close interaction of advisees with their advisor leads to enhanced satisfaction level with the institution and reduces attrition rate [8].

The third advising task is the most crucial one as it is directly related to student success in the academic journey. It involves a pre-emptive check to follow up on students' academic progression, especially the students who are struggling with their studies. The advisor identifies and provides support to students who are at risk. The support may involve arranging a meeting with the counselor or facilitating tutorial sessions through the academic success center, or more. This type of advising has a significant impact on student retention and persistence [11].

### A. *Knowledge Management and Academic Advising*

Knowledge management (KM) activities are at the core of the academic advising process. Therefore it is essential to understand KM and its application within the various advisory tasks. As new faculty members, and thereby advisors, join the institution, and current advisors leave, it is crucial to ensure that knowledge is captured and stored adequately to prevent knowledge loss. This section describes the KM processes and mechanisms involved in the advising process at the institution of study.

KM processes are the methods used to create, share and utilize knowledge within an organization. Study [12] identified four main KM processes - knowledge discovery, knowledge capture, knowledge sharing, and knowledge application. These processes are encompassed in all the advisory tasks as described below.

Knowledge discovery is the process of acquiring knowledge from various sources to make decisions, solve problems or generate new knowledge. Advisors use various sources of information such as the program structure, course requirements, and student's academic portfolio to build a customized plan for each student. They often brainstorm with other advisors and attend training to acquire knowledge related to this task.

Knowledge capture is the process of storing the acquired knowledge in a format that is readily available for those who need to access it. Advisors store the advising plans they have created in a student information system and share them with their advisees. However, a lot of the communication during this process is also captured in an unstructured format such as email, and in-person and phone conversations making it challenging to access and utilize this knowledge effectively in the future. Knowledge is also captured in the form of documentation of the policies and procedures of advising and is stored in the employee portal and communicated via email.

Knowledge sharing is the process of sharing tacit or explicit knowledge with other members of the institution. Advisors share their knowledge with advisees in the form of counseling, advice, and recommendations when performing advising tasks.

Moreover, advisors also share their best practices through informal and formal professional development sessions organized at the institution.

Knowledge application is the process of utilizing the knowledge to solve problems and perform tasks. Advisors use directions and routines to apply their knowledge based on the problem at hand and advisees' maturity level. For example, when dealing with new advisees, advisors direct the students on what courses to take in the first semester. As the advisee's maturity level increases, advisors guide the students by explaining how to choose courses and plan their studies.

Knowledge may be further subdivided into two main types –tacit and explicit knowledge. Tacit knowledge resides in the individual's mind in the form of experience, insights, and wisdom and is difficult to transfer, while explicit knowledge is documented and stored in a format that can be shared, understood, and applied. Reference [13] developed the spiral SECI model to explain how tacit and explicit knowledge interact with each other to create new knowledge. The model consists of four phases – Socialization, Externalization, Combination, and Internalization. Fig. 1 shows the tasks of advising in each phase of the SECI model.

The socialization phase occurs when advisors mentor the advisees using face or online meetings, share best practices with their colleagues, and attend professional development sessions to understand new technologies or requirements for advising. Socialization facilitates knowledge discovery and knowledge sharing processes. In this phase, tacit knowledge is used, which is largely based on experience, and advisor intuition.

The externalization phase occurs when tacit knowledge is converted into documented form. In the advising process, the registration department publishes policies, manuals, guidelines. The admissions department provides documentation on the program structure and student academic performance. The advisors utilize this information for effective advising. Although the general knowledge of advising is captured in the documentation, the specific knowledge that the advisors possess when dealing with various cases is lost, as the advisors are not required to externalize their knowledge on advising cases they have dealt with.

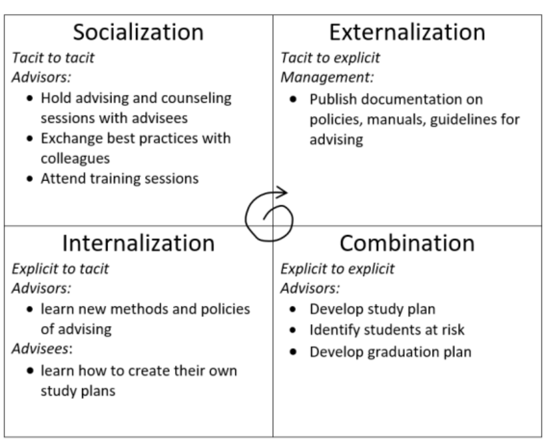


Fig. 1. SECI Model of Advising Tasks.

In the combination phase, the advisors integrate the explicit knowledge from various documentations to develop a customized study plan for every student and a graduation plan for final year students. The advisors also use the information to identify students at risk. Finally, in the internalization phase, the advisors learn new policies, methods, and systems essential for effective advising and students internalize the knowledge shared with them to create their own study plans.

This section provided an introduction to the paper, along with background information on the organization of the study and the role of KM in the advising process.

## III. Problem Identification and Analysis

### A. A KM Perspective of the Advising Challenges

People, processes, and technology are the three main interdependent elements of KM activities in an organization. The systematic integration of these three elements is essential to effectively implement KM practices in the organization [14], [15]. The current advising process at the institution of study has several limitations with regards to all these elements that hinder the integration of successful KM practices for the advising process. This section discusses the main challenges of the advising process.

*1) People:* People are the most essential element of KM practices in an institution as they are the possessors of knowledge. The people involved in the advising process are the advisors, students, and management staff. One of the main challenges is that the advisor does not have time to provide personalized advising to each advisee. The advisor's workload, of 20 teaching hours per week and involvement in research activities and other several administrative tasks, does not leave sufficient time for personalized interaction with 25 to 30 advisees. This has an impact on several tasks such as supporting students who are at risk, and maintaining a good level of communication and interaction with the advisees. The academic performance of a student is highly impacted by the quality of advising [9].

Another challenge is that new advisors do not have sufficient knowledge about the advising process to effectively advise students. Advisors must be aware of institutional policies, program structures, and academic requirements. Moreover, new faculty do not have the experience that advisors accumulated over the years. An inexperienced advisor does not have sufficient expertise to handle difficult cases such as students who have changed their programs and require course equivalency, or students on probation who need special attention in terms of planning courses. Erroneous advice in such cases may lead to a student repeating courses or taking courses that will not improve the GPA of a student on probation.

Communication between individuals in the advising process is vital to effective advising. Students are often shy to approach their advisors for queries as they do not know them personally. On the other hand, it is also observed that student queries are often repetitive relating to institutional policies and procedures such as registration times, applying for missed assessment, following up registration, etc. Their general queries and concerns often go unaddressed, which in turn influences the student satisfaction level and integration at the institution. Moreover, advisors do not have the time to get to know each advisee personally. The lack of timely communication and interaction between advisee and advisor is a common challenge faced at the institution as it influences knowledge sharing negatively.

*2) Process:* The advising process includes tasks that are required for effective and efficient advising to capture and store the knowledge involved therein to make it available to those who need it. The SECI model for academic advising described in Section II, shows that the process of knowledge externalization is inadequate. Currently, the only form of documented explicit knowledge is provided by management in the form of manuals, policies, program requirements, and more. The knowledge accumulated by advisors over the years is not captured and shared in any formal way. This knowledge would be beneficial to both new advisors and current inexperienced ones. Furthermore, there is a risk of the knowledge being lost when a faculty members changes or leaves the job.

*3) Technology:* Technology acts as a supporting mechanism to facilitate the effective distribution and storage of knowledge to retain captured knowledge within the organization and make it available to individuals who need it [13]. At the HEI of study, several technologies are used to manage the information that is required for making informed decisions. For example, the advisee's academic performance data is stored in the banner system and available as reports for the advisor, the policies and procedures are stored in the SharePoint portal, and a degree audit system is used for managing and creating an advising plan. Moreover, email is also used for communicating new information, and requirements for advising. A lot of time and effort is spent in discovering knowledge from various sources for each student as these technologies are dispersed in different applications and not integrated.

Crucial information that is required by the advisor to track student progress and identify students at risk is currently not available during the semester. For example, the student's current semester's academic performance and attendance records are accessible by their teachers only. Due to this reason, advisors are unable to take pre-emptive measures at an early stage for an advisee who may be at risk of failure. Remedial actions are taken too late after the student has already failed the course.

The current system also does generate notifications to the advisor that are essential for their decision-making process. For instance, when an advisee drops the course or fails due to attendance, the advisor is not informed. This information is essential to modify the proposed study plan as it becomes a priority for the student to repeat the failed course to raise the GPA. At the end of the semester, when plans are updated based on student performance, the advisor has to manually check each student's academic record to update the student's plan.

TABLE I. ADVISING CHALLENGES AND ITS IMPACT

| KM Element | Challenge | Impact |
|---|---|---|
| People | Lack of time | Advisors are unable to provide personalized advising and support to each advisee |
| | Lack of knowledge | Erroneous or inadequate advice by advisors, which may influence students' academic progression. |
| | Poor communication | Students find it challenging to integrate within the environment |
| Process | Lack of externalization | Organizational memory loss, advisors knowledge is not retained and shared in a formal way |
| Technology | Lack of structure | Knowledge is not captured in a structured format. Often involves email communication |
| | Lack of integration | Information is dispersed, requires time and effort to get access various information sources for decision making |
| | Lack of information availability | Advisors cannot take pre-emptive decisions and support advisees at risk at an early stage |
| | Lack of notifications | Cannot provide support at an early stage. Time-consuming to check each advisees' academic progression at the end of the semester. |

Table I summarizes the advising problems faced at the institution of students and its impact on the institution and its members. The challenges highlighted below are the cause of inefficiencies in the advising process.

A software system is crucial to addressing the challenges of academic advising described in the previous section. Technology has the potential to automate tasks, reduce advising errors, improve communication, and provide insights on students' progress. To this effect, Artificial Intelligence (AI) based technology solutions offer a promising avenue to address the challenges of the current advising process. The AI-based tools can automate the low-impact tasks to reduce the workload of advisors and provide insights for key tasks to support better decision-making [16]. Moreover, AI also has the potential to enhance students' experience through machine intelligence supported by human advisors [9].

Fig. 2 presents a visualization of the analysis of terms in research studies related to AI in higher education over the last two decades. The visualization, constructed using VOSViewer depicts the relationships between frequently occurring terms in the research papers in the form of a network diagram [17]. Three main clusters are evident in the diagram. The red cluster shows that data mining is the predominant study in HEIs, which has been investigated by a vast majority of authors. The blue cluster shows that the main techniques researched are machine learning algorithms. The studies on academic advising are very limited. In addition to this, the studies that have investigated academic advising have only examined one aspect of advising rather than providing a comprehensive AI solution that tackles all the advising problems.

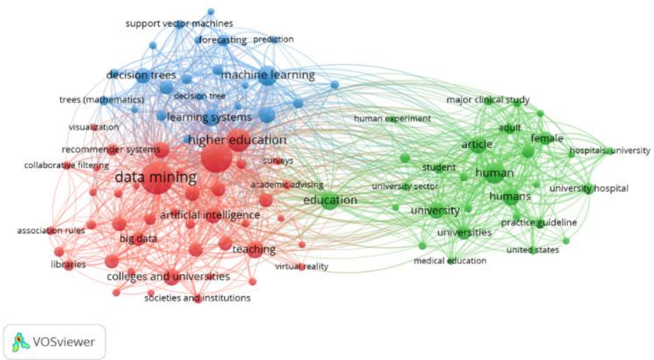


Fig. 2. VOSViewer Analysis of Terms.

This study proposes AI-based technologies that offer a comprehensive solution to make the advising process more effective and efficient. At the institution of study, the following three main tasks of advising have been identified that can be automated using AI-based advising tools to alleviate the underlying problems described in this section:

- Developing personalized study plans
- Early identification of students at risk
- Provide personalized assistance to students.

## IV. Literature Review

This section provides a critical review of the use of AI-based solutions for advising in the existing literature. The review focuses on the three main advising tasks outlined in the paper. Several studies have investigated AI-based advising solution that merely examines one area of advising, while only a few have applied AI solutions to multiple advising tasks. Thus, this section reviews studies by categorizing them based on the type of AI solution proposed by reviewing studies that have focused on a single aspect of advising and those that have used AI-based solutions for more than one advising task.

### *A. AI-Based Solution for Study Plans*

Numerous papers have researched the use of AI for creating study plans or recommending the ideal courses for students to maximize success. While some studies focus on rule-based systems, others are based on machine learning algorithms for recommending ideal courses to students that maximize their success.

A data-driven model is used by [18] to create a predictive analytics tool that supports academic advisors in advising decisions based on insights from historical data. They use a web application with a rich dashboard interface to display the chances of student success in the selected courses along with the details of the prediction. A multilevel clustering algorithm is used to predict the success rate in each selected course based on previous students' academic performance data such as course grades and the number of courses registered in a semester. The authors used a comparative study to verify their system in two universities. The participants of the study, experienced and inexperienced academic advisors, used traditional methods and the predictive analytical tool to perform advising for several cases. The results of the study showed that advisors explored more course options when using the AI-based tool to develop a suitable study plan with lower failure risk for each student. The main limitation of the study is that it relies on the academic advisor to select the courses for the student and the system merely provides a success rate of the selected courses. The system relies on the adivsors knowledge of institutional, course, and program requirements for selecting ideal courses.

Reference [19] proposed an intelligent advising system that assists students in course registration. The system is intended to be used by students without the need of a faculty advisor. Students are recommended courses based on their current performance, known preferences, historical data, and academic policies. The proposed advising system integrates with the current information system for the academic data required for predictive analytics. The system uses association rule mining to explore patterns in the academic dataset to identify the group of courses that should ideally be taken together. A rule-based expert system is used to assign a priority score to the courses based on academic policies and factors such as student GPA and nature of the course (prerequisite course, core or elective course etc.), course grade, and more. Finally, a recommendation algorithm is used to suggest courses to the students. A limitation of the study was that it considered student preference as a major factor in the recommendation model, but failed to describe the features used to determine students' interests. Moreover, the proposed model was not evaluated for the quality and accuracy of the recommendations.

Another model proposed by [20] recommends courses to university students based on personal traits and academic data. Student personal characteristics include features like gender, age, knowledge level, learning style, the term of study, and performance. The academic data consists of features such as courses, credit hours, semester of study. The proposed model uses a knowledge-based model to assign weights to selected courses based on the students' performance. The study does not apply institutional policies, course, and program requirements when recommending courses.

Study [21] designed an interactive system to recommend suitable courses to university students based on their interest and popularity of the course. The recommendation is based on historical enrollment data, course descriptions, topic, instructor, and time of study. A student searches for the offered course using keywords and may filter the popular course recommendations by providing preferences such as time of class, topic of interest, and more. The system has several limitations. First of all, it does not integrate with the current information system. Recommendations are not based on students' academic history or performance. Second, the system is only suitable for universities with a flexible curriculum where a student is free to explore and take various courses across different departments.

Both [22] and [23] developed a rule-based expert system that recommends courses for university students. The expert system rules are based on course pre-requisite requirements, year of study, and course eligibility. The system provides a rationale for each recommendation. The study [23] does not integrate the system with the data stored in the student information system. The student is required to provide the courses they have completed, their current GPA, and their major as input to the system. Moreover, failed courses are not taken into account when making the recommendation. The research [22] integrated the expert system with data extracted from the institutional database. However, the system does not prioritize the recommended courses according to the importance of registration in the following semester.

### B. AI-Based Solution to Identify Students at Risk

The use of machine learning algorithms to develop automated intervention systems that integrate with a learning management system (LMS) has been investigated by several researchers. Students' engagement in the online environment and their current academic performance can be used to predict course outcomes at an early stage [24]. Furthermore, studies have also shown that timely interventions and support for low-performing students are effective to help them manage their study patterns [25].

Study [26] used machine learning and deep learning algorithms for the early identification of students at risk using data collected from an online learning platform. The study predicts student failure at various stages of course completion based on the student demographic data, performance, and engagement data using click patterns. The study shows that the random forest algorithm performed the best with up to 92% precision, recall and accuracy. The study further recommends intervention strategies at the various course completion stages based on prediction outcomes by sending messages of encouragement, recommendation, or fear to students at risk. The study does not consider the involvement of the advisor or instructor in supporting underperforming students. Students who are at risk may not possess the mental or emotional capability to comprehend the motivational intervention messages. The involvement of the advisor is essential to determine the support a student may require to improve his performance.

Reference [27] used deep learning to identify students at risk of drop-out at an early stage in an online course. The study uses click patterns, discussion, and quiz scores to create prediction models using SVM, KNN, decision tree, and deep learning algorithm to predict student dropout at a weekly rate. The deep learning algorithm performed best with an average AUC (area under the curve) rate of 96%. The study further went on to suggest intervention strategies based on the probability of course dropout, such as varying levels of support by the instructor.

Both the studies [26], [27] were based on Massive Online Open Course (MOOC) dataset, that have a large number of enrollments and thus a huge dataset that is required for deep learning. On the contrary, enrollment in degree programs will not have the same dataset size collected from the virtual learning environment. Moreover, the models were not tested on different sized datasets for the generalization of results.

Study [28] used clickstream data collected from an ebook interaction log, along with student performance at various stages in the course to predict student performance. Comparisons of prediction accuracies during various weeks of the course showed that the earliest reasonable accuracy, of 79%, is achievable as early as week 3. The study is based on the assumption that the ebook is the main resource used by all students in the online learning environment. Furthermore, the study did not utilize data from the existing information system to generate the predictive model.

Eight machine learning algorithms were used by [29] to determine the optimal time during a semester-length course to predict student grades. The study uses student demographic data, academic data, weekly assessment scores, and LMS interaction data to create a prediction model. Weekly predictions revealed that the earliest reasonable prediction rate is achievable by week six to support early intervention for poorly performing students. The study relies on continuous weekly assessments for predictions, which is not applicable in most courses. Moreover, the study integrated LMS data with student admission and academic background data but did not consider attendance as a feature for prediction.

### C. AI-Based Solution for Digital Assistance

With today's technological advancement students are constantly in need of information for their daily tasks and academic progression. Providing adequate channels for student communication is vital to help students integrate with their environment and feel connected and enhance student satisfaction. Students often have queries about the institutional and academic policies and procedures, academic progression, activities, and more. In reality, the student services team and the academic advisors are usually overwhelmed with such a large number of queries that they are not able to provide instant responses. As a result students' disconnection and dissatisfaction with the institution increases.

Chatbot systems have the potential of providing students with the information they need by answering their queries in a conversational style. They provide 24/7 service, unlike human advisors. Despite the numerous benefits of chatbots in improving levels of service, the use of chatbots in HEI for advising is very limited [30]. This section reviews the AI-based solutions that have used a chatbot system for improving communication and answering student queries.

Study [31] designed a rule-based expert system that answers students' queries on institutional policies and guidelines to familiarize students with the environment. The digital assistant, built with CLIPS and JAVA, uses both forward and backward chaining and is based on inference rules. The knowledge base for the expert system was gathered from the website, student feedback, and experts in the institution. User queries were classified into four categories – yes/no, what, where, and when questions. The automated virtual assistant was tested completeness and correctness using 70 participants and resulted in an accuracy of 99%. The main limitation of the study is that the chatbot system does not support conversational AI. The question type has to be selected from a predefined list. Interaction with natural language processing would be more intuitive and adaptive for end users.

An intelligent academic advisor using a DeepQA system built was built by [32] using IBM Watson. The system was used to answer queries from potential, new, and, current students as well as faculty members pertaining to academic advising in a business school. The intelligent system was initially populated with a database of nearly 300 questions and answers, and other information extracted from FAQs, syllabus, and more. Moreover, the intelligent system has an engine to learn and increase its knowledge base. The chatbot does not provide personalized feedback to students.

Reference [33] used a conversational agent to support administrative tasks of recruiting students into degree programs. The AI system matched student skills to the program requirements by asking questions and using keywords from their answer to select suitable programs. The admin staff also utilize the system to query information about shortlisted candidates. The system was not designed mainly for administrative purposes and not for advising.

Study [34] used a chatbot to ease the process of selecting elective courses for a degree program in computing. The chatbot uses natural language to answer queries related to the courses, provide peer reviews about the courses, analysis of choices, and provide a personalized recommendation based on the student record. The chatbot had a very specific use and did not provide advising in other matters of academic life.

Reference [35] used a chatbot application, developed using the IBM Watson API, to provide support to students struggling in programming. The chatbot not only provides support for programming related queries, but also for personal issues such as depression, suicidal thoughts, etc. It directed students to the appropriate department call center for their issues or calls the ambulance based on the severity of the case. The chatbot was designed to detect student frustration while studying programming. It did not provide general assistance in other college related matters.

### D. *AI for Multiple Advising Tasks*

Some studies investigated an AI-based solution for more than one aspect of advising. Latorre-Navarro (2014) developed an AI-based solution that answers student queries and recommends courses. A conversational agent was used to answer questions on a wide range of topics related to academic policies, procedures, and services. The authors also used an expert system that guides students to create their study plan and sends it to the advisor for approval. The main limitation of the system is that it is not integrated with the information system. Students are required to provide their academic progress such as current courses, failed courses, and completed courses. An error in providing this information could result in an incorrect plan.

An intelligent web-based advising system that supports effective advising was developed by [36]. The system is designed to be used by both advisors and students. A rule-based expert system is integrated with the current information system to extract a student's academic record and create a study plan for the following semester and view the graduation status. The system also answers basic queries related to institutional policies. Advisors can also use the system to view their advisees' profiles, and get access to all the advising documentation integrated in a single location. Notifications are sent to the advisor when there is an update to a policy, ensuring that all advising decisions are accurate. A limitation of the study is that it does answer any personalized queries or send reminders notifications to students.

Though both studies [16], [36] tackled more than one advising problem by leveraging AI-based technologies, yet they do provide a comprehensive solution. The studies did not investigate one of the main tasks of advising, which is to identify and support low-performing students with early intervention strategies.

An overview of the literature shows that, to the best of the author's knowledge, no study exists that provides a holistic advising solution using AI technologies to addresses all the challenges of advising faced at an academic institution. Hence the purpose of this study is to fill the gap in this area and recommend a comprehensive AI solution for the institution of study.

## V. Identification and Evaluation of Alternate Solutions

This section discusses three AI-based solutions proposed for the institution of study – (1) AI-based solution for creating study plans (2) AI-based solution for identifying students at risk of failing a course at an early stage, and (3) AI-based solution for personalized digital assistance. All solutions are integrated with the institutional database to provide personalized information to the students to support their academic progression. The study proposes the use of a rule-based expert system to create ideal study plans, a machine learning model to identify students at risk, and a chatbot system to provide personalized digital assistance. Fig. 3 shows an overview of the proposed solution.

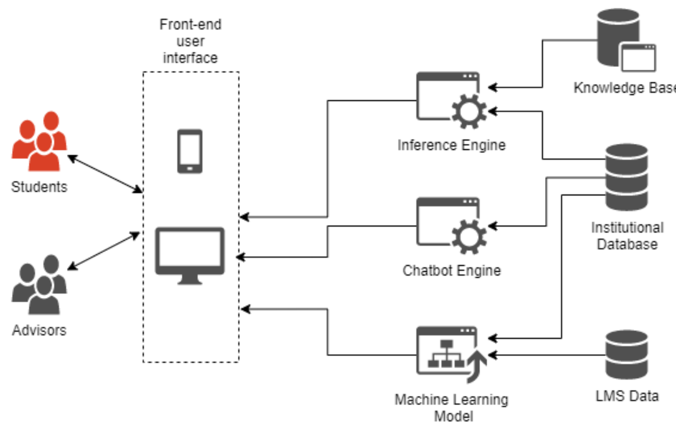


Fig. 3. Overview of Proposed Solution.

### A. *AI-Based Solution for Creating Study Plans*

Studies have investigated the use of machine learning for recommending courses to students [21] as well as including features personal traits [20], and student preferences [19]. While this type of model is suitable for online courses with a large number of enrollments and course choices, this model does not work for the institution of study. The courses offered at the current institution are based on a program requirement that has a predefined number of courses with a few electives. The courses that must be taken according to the ideal semester plan, obeying the rules such as course sequence in the program structure, minimum and maximum required credits (with the program area), catalog term, academic progression of the student, and more.

To this effect, this study proposes a rule-based expert system that captures the knowledge of domain experts to create a knowledge base. The expert system utilizes student data from the institutional database and applies registration rules and policies to recommend a list of ideal courses that maximize the chance of students graduating on time. Fig. 4 shows the architecture of the expert system.

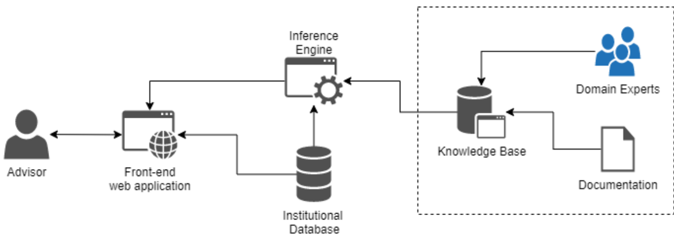


Fig. 4. Rule-Based Expert System.

The knowledge engineer will acquire the knowledge from domain experts such as the registration staff, and expert advisors to build a knowledge base. All the policies and registration requirements are also encoded as rules with the system. The system uses student academic data, program data, and course data from the institutional database as initial facts to map the student course requirements against the program requirements and applies the rules to identify a list of ideal courses.

- Student Academic Data consists of the catalog term, the program of study, placement scores, list of all completed courses, failed courses, and credit hours completed.
- Program Data consists of the requirements of the program such as the total credits required in each area (core courses, elective courses, concentration courses, and general studies courses).
- Course Data consists of the credit hours of the course and the pre-requisite(s), co-requisite(s), and equivalent courses.

The inference engine applies the knowledge base rules to the student, program, and course data that are the initial facts in the working memory. The eligible courses are assigned a priority based on the importance of completing that course in the following semester. For example, a higher priority is assigned to a course in which the student previously failed, or a course that is a pre-requisite of other courses in the following semester. Finally, a web-based interface is used to present the study plan to the advisor, in order of priority. The advisor analyzes the plan that is created by the system and makes any necessary modifications and advises the student accordingly.

### B. *AI-Based Solution for Identifying Students at Risk*

Machine learning algorithms have been investigated in numerous studies to identify students at risk at an early stage during course progression. Some studies relied on LMS click patterns to predict low-performing students [26]–[28]. LMS interaction requires interacting with the course content online, which in turn generates a click pattern that can be analyzed for student engagement within the course. This model is not appropriate for the institution of the study, as most of the courses are face-to-face. Students mainly use the online environment to download course resources, attend online sessions, or submit assessments. Click patterns would not be an ideal indicator of student engagement especially when the student is using the course resources offline.

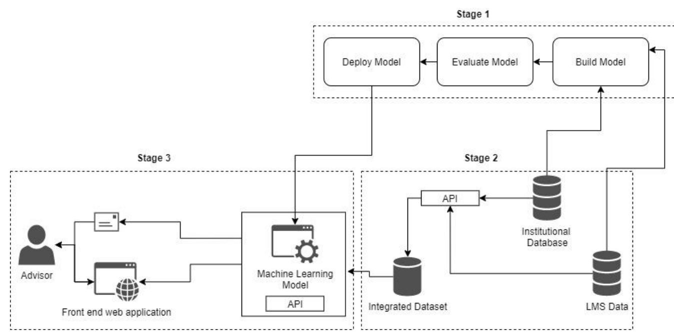


Fig. 5. Mahcine Learning Model for Identifying Students at Risk.

To this effect, this study proposes the use of course performance data and student academic history to predict the risk of failing a course. The proposed system will be used to low performing students as early as week six so early intervention strategies can be engaged. Howard et al. (2018) showed that reasonable machine learning performance can be achieved at week 5-6 to predict course attrition. Fig. 5 shows the architecture of the proposed advising system.

The system integrates LMS data and institutional data to build a machine learning model. The main elements of the system are explained in three stages:

*1) Build and deploy the machine learning model:* In this stage data historical is extracted from the institutional database and the LMS at the beginning of the academic year. The institutional database contains the following data:

- Students enrollment records that include the high school score, IELTS score, placement test scores, gender and status (working or not), and other profiling information
- Academic data such as program of study, credit hours completed, credit hours registered, courses completed, overall GPA, and attendance record.

LMS Data contains the coursework assessment data. Coursework assessments are usually conducted at regular intervals – week 6, week 12, week 15. The final assessment is scheduled on week 16.

In stage 1, the machine learning model is developed using historical data of the last 4-5 years. The data will be pre-processed and used for training and testing multiple machine learning algorithms. Several machine learning algorithms will be used and evaluated to determine the best performing algorithm suited for the data provided. At the end of this stage, the machine learning model will be deployed for use with the current records. This stage will be repeated once every academic year for monitoring and tuning the model to generate a new model based on new data acquired in the previous year.

*2) Integrate LMS and institutional data:* In this stage, the current semesters academic record is extracted from both the institutional and LMS and integrated into a dataset. It is recommended that the extraction takes place at week 6, week 12, and week 15. Based on the findings of previous researchers [28], [29], it is expected that good prediction rates of at-risk students are achievable by week 6.

*3) Apply the machine learning model to generate a prediction:* In this stage, the deployed machine learning model is applied to the extracted data of the current semester to determine students at risk of failure. A web application is used as a front-end interface for advisors to view the risk profile of their advisees. The system also sends notifications about advisees that require immediate attention.

### C. AI-Based Digital Assistant

A conversational AI-based solution provides timely response to students' academic queries and improving the students' experience. Several studies have investigated the use of chatbots in an educational setting, however, the main purpose of the system was either administrative, such as recruiting students [33], or recommending courses [34]. Moreover, the studies that used chatbots for answering student queries [31], [32] did not integrate it with student's academic record to provide personalized information. None of the chatbots proposed in the reviewed studies send push notifications to students.

This study recommends the use of a conversational AI chatbot that integrates with the institutional database containing student's academic history, registration schedules, program requirements, course requirements, and a knowledge base of frequently asked questions. Unlike a human advisor, the chatbot will be available 24/7 to respond to various student queries. It will respond to general queries and personalized queries using the student's academic data. Furthermore, the chatbot will also initiate reminders to the student about general information such as upcoming deadlines, and initiate personalized reminders such as high absences rates to ensure that the student does not miss more classes. The notifications may also be personalized to the student's interest such as sports, clubs, and more.

Examples of general student queries are:

- When is the deadline for dropping a course?
- What is the pre-requisite for CIS 2203?
- How can I change my program?

Examples of personalized student queries are:

- What is my CGPA?
- How many volunteering hours have I completed so far?
- How many absences do I have?
- Who is my advisor?

Example of general notification:

- Add and drop period ends on Sunday, 10th October

Example of personalized notification:

- You have reached 7% absence in the advanced programming course.

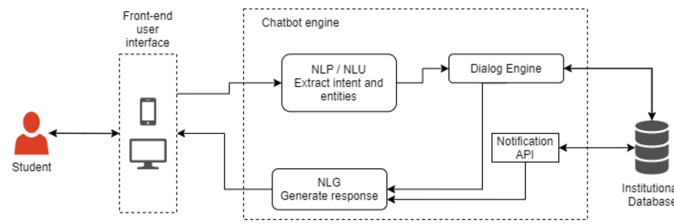


Fig. 6. Advising Chatbot Architecture.

Fig. 6 shows the proposed chatbot architecture. A brief explanation of the architecture is given below:

- The student writes a query in natural language using the chatbot client interface.
- The chatbot backend processes the query using a NLP (Natural Language Processing) engine, which converts the written text to structured data.
- The NLU (Natural Language Understanding) engine then extracts the intent and entities from the given structured query.
- Based on the processed query, the dialog engine of the chatbot retrieves the data from the institutional database and presents the response to the NLG (Natural Language Generator).
- The NLG processes the structured response into natural language and presents it to the student via the front-end interface
- The chatbot engine also contains an API, linked to a scheduler, which retrieves data from the database to send timely reminders and notifications to the students.

The proposed advising system reduces the workload of advisors by automating repetitive and mundane tasks. Advisors can spend their time getting to know their advisees and supporting them in their personal and career growth. The benefits of the proposed AI-based solution are summarized in Table II.

TABLE II. ADVISING CHALLENGES AND ITS IMPACT

| AI-Based Solution | Benefits |
| --- | --- |
| Rule-based expert system for creating study plans | • Integrates with the existing information system to use accurate data of current student records, academic history, registration, and academic policies.<br>• Minimizes/eliminates erroneous decisions of new or inexperienced advisors<br>• Reduces workload of advisors |
| Machine learning model for identifying students at risk | • Provides early identification of students at risk before it is too late.<br>• Support students with early intervention strategies that can possibly alleviate the risk of failure |
| Conversational AI chatbots for digital assistance | • Constant availability of support to students enhances student experience and increases loyalty towards the institution.<br>• Provides equal opportunity for all students to ask questions, at any time 24/7<br>• Access to personalized assistant<br>• Students are encouraged to stay on track with nudges from the system such as reminders |

## VI. CONCLUSION

Academic advising is a vital function in HEIs for providing guidance and support to students throughout their academic tenure [5]. Effective advising not only has a significant impact on students' academic performance but also has a positive influence on the overall academic experience [37] contributing to academic retention and persistence. The imperative nature of academic advising makes it crucial for institutions to invest in tools that support advisors in managing advising tasks effectively. This study explored the practice of academic advising at an academic institution based in the UAE. The study investigated the advisory process and the limitations under the umbrella of Knowledge Management. Finally, AI-based technologies are proposed to provide a comprehensive solution that automates advising tasks. AI-based systems can guide students through their journey with little intervention from the advisors, thus reducing the workload of advisors from menial tasks to focus their effort on key advising tasks such as development advice and career planning. Moreover, AI-based advisory systems may be personalized for individual student need and provides an equal opportunity for all students to access the information and service that they need.

The problems of academic advising are highlighted in this study from the perspective of the three KM elements - people, processes, and technology. Students and advisors are the people involved in the advisory process. The ratio of advisor to advisees makes it challenging for advisors to provide personalized guidance to each advisee. Moreover, an advisor's inexperience or lack of knowledge may lead to erroneous advice. Student queries often go unanswered leading to dissatisfaction and frustration. The advisory process involves creating study plans for students, dealing with issues, guiding and counseling students. An experienced advisor's knowledge is currently not captured in any formal way and may lead to organizational memory loss when the advisor leaves the institution. The current technologies at the institution are inadequate in supporting all the KM processes involved in advising effectively. The information is dispersed in different systems making it inefficient to look up for each student. Advisor's time and effort are consumed in analyzing student data, to create study plans. Furthermore, advisors need to set meetings with advisees, send reminders, and follow up on failed courses. Moreover, the current system does not provide insights to identify low-performing students so pre-emptive measures may be taken to manage the course of their studies.

The study proposes three AI-based systems as a comprehensive solution to alleviate all the problems associated with the current advising process – (1) Rule-based expert system for recommending courses and developing study plans for the following semester (2) Machine learning algorithm for identifying students at risk of failing a course at an early stage, and (3) conversational AI chatbots to provide personalized digital assistance to the student. All three systems integrate with the data in the current information system to provide personalized support and guidance to students and advisors. The systems are promising in terms of reducing the advisor's workload and improving student satisfaction with the institution, leading to student retention and persistence as an overall goal.

### A. Limitations and Future Research

This study provides a framework for leveraging AI technologies in academic advising and focuses only on the three main tasks performed by an academic advisor. An avenue of future research is to investigate the implementation of the three systems as a prototype and a proof of concept. The systems must be verified for accuracy and quality of results.

One of the aspects of advising that is not considered in this study is the guidance provided to students during the enrollment stage to choose a program of study. This type of advising is done by the admission department and is crucial as most students are undecided about their career pathways when they enroll. Furthermore, studies have shown that students often receive inadequate guidance to make the right program choice, which in turn leads to changing programs during their studies [38], thus delaying graduation. In some cases, it may also lead to dropping out due to lack of interest or inability to cope with the program requirements. Machine learning algorithms may be investigated for recommending ideal programs to students that maximize their chances of success.

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