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Artificial Intelligent Based Adaptive Recommender System

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Abstract

The challenge of indecision among humans cannot be completely eliminated. This leads to the necessity of addressing questions such as what, which, where, who, and how as issues. Therefore, when situations take a negative turn, the problem of identifying the right person to communicate with becomes pivotal. Many individuals are burdened by concerns related to security, social risks, and other similar factors. As a result, they tend to isolate themselves and make decisions that might not be rational. Academic advising stands as a crucial endeavor within educational institutions. It assists students in exploring potential career paths, academic fields, and opportunities within the college setting. This project has the objective of addressing the widespread issue of student failure and university dropouts. It involves the creation of an AI-driven student portal recommender system designed to tackle well-known human challenges autonomously, without requiring direct human intervention. Recommender systems offer users' individualized needs by leveraging Artificial Intelligent (AI) techniques, computational intelligence and machine learning algorithms which recommend to users what materials to learn by on psychometric assessment result and possible other individual characteristics then suggest relevant items to user in term of its preferences. Consequently, the integration of AI-based systems has emerged as a solution, allowing machines to emulate human thinking and tackle real-world problems. Addressing the questions of what, which, where, who, and how is crucial because the inherent complexity of human desires cannot be easily resolved in determining the next action. A diligent and growth-oriented student must make informed decisions regarding which courses to pursue, what materials to study, when to engage with them, and how to approach the learning process. By reflecting on past actions and considering current preferences, students strive to achieve these ultimate objectives. To aid users in their decision-making, recommender systems filter out unnecessary information, provide guidance and recommend to user based on the specific context. Personalization method was adopted as a technological tool for critical human complex reasoning, which provides students with proactive and intelligent access to information, taking into account past performance and current preferences. This is made possible through the use of MySQL, an open-source database tool, for the application's backend, and high-level programming languages like PHP, AJAX, and JavaScript for the frontend. These technologies enhance prediction accuracy and address challenges such as sparse data and the cold start problem. The application is employed to create a personalized and intelligent recommender service for students. A scheme based on machine learning is proposed, which involves traditional statistical analysis and collaborative filtering techniques to discover personalized explicit interests from user data. Furthermore, machine learning methods are utilized to identify users' current demands, analyze demand features, and analyze demand trends. It is important to acknowledge that recommender system may occasionally be incorrect, leading to disappointment. Privacy concerns related to profiling can also contribute to such dissatisfaction. To ensure students find the most suitable options for their needs, we propose a method that allows them to connect with a human representative.

Keywords: ***Artificial intelligent; Intelligent recommender; Machine learning; Personalized.***

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1. Introduction

The regular functioning of Artificial Intelligence, like the recent AI model CHATGPT, relies on user interaction [1]. If a user does not actively engage with this application, specific issues might not receive much attention. This has posed a challenge because modern-day students often seek immediate and proactive guidance even without active interaction. As a result, this study aims to concentrate on developing a personalized AI model that can provide advice to students using existing information about them and their surrounding circumstances.

Academic advising is essential for creating a warm and relevant learning environment for college students. Academic counselors have a difficult and time-consuming job because of how quickly educational institutions change their degree requirements and programs. Despite these dangers, academic confidant always tries to provide accurate, timely, and consistent guidance [2].

With the ability to provide individualized guidance aimed at effective and efficient learning, a solid academic advising system is nowadays an essential component of learner success. This is due to the fact that credit-based education is becoming more and more significant in today's educational environment. The educational system must therefore surely advance even more fast than the current system. Since many people are affected by it starting at a very young age. Therefore, such a well-polished system would be a remarkable step for this sector as it provides a matrix connecting its numerous divisions and aids in bringing together information and educational societies [3].

Common methods for assisting users in making decisions include filtering out information that they might find unneeded and offering advice and suggestions on what to do at a certain time.[4] An institution with thousands of students will make recommendations for each and every one of them, which can be time-consuming and result in recommendations that are unproductive. An AI-based recommender system can be useful in this situation [5].

Recommender systems are intelligent systems created to foresee the preferences or interests of users of a certain system. Recommendations have a big impact on every human existence. People choose their ideas based on other's recommendations.

As a result, they placed more importance on the advice. A system called a recommender system was created to make recommendations. In modern Institutions, recommendation-making systems are essential. Many schools employ recommender systems to advance institutional goals. They might set up their courses so that one benefits more than another in order to entice more students. A variety of ranking and recommendation systems have been developed to rate the best course recommendations for students to receive. Ratings, either explicit or implicit, are computed. In this study, an adaptive student recommendation system is made using AI.

2. Review of Related Work

Philosophers initially established the groundwork for contemporary AI as they aimed to elucidate human cognition through the automated manipulation of symbols. This progression culminated in the emergence of programmable digital computers during the 1940s. Rooted in mathematical logic, this device ignited the notion within the scientific community of constructing an electronic brain. [6]

Mathia, an AI-driven platform developed by Carnegie Learning, provides tailored math education for middle and high school students, guaranteeing enhanced understanding of mathematical principles. [7]

Step Wise, created by Quadrium Corporation, offers instant feedback and adaptive learning in STEM disciplines, a feature believed to enhance student achievement. [8]

Finally, Congii’s educational platform harnesses AI to deliver individualized tutoring and evaluations across diverse subjects, fostering a more profound comprehension. [9]

The rapid advancement of AI technology has resulted in several innovative AI programs appearing in recent years. ALEKS, an adaptive learning system, offers personalized instruction in mathematics and chemistry, enhancing the learning experience of students. [10]

The integration of AI technologies in education has become an expanding reality, and ChatGPT represents the most recent advancement in this evolutionary process. With the progress observed in computational capabilities and data analysis, AI algorithms are becoming increasingly intricate, possessing the capacity to autonomously learn and enhance them.

The idea of compiling the feedback of millions of internet users in order to find more relevant and alluring articles first emerged in the early 1990. Users could manually search for objects in a domain of online content using Tapestry. One of the first steps toward an automatic recommendation system could be seen in the computerized librarian. Grundy used comparable techniques to identify a specific user's interests by using internet articles based on user activity to provide a tailored recommendation. In the late 1990s, academics studying human-computer interactions, machine learning, information retrieval, and other related fields became interested in Recommender System. As a result, many recommender systems have been developed for a wide range of application domains, including Jester. For humor, the Bell Core Video Recommender for movies, and Ringo for music. In the same period, numerous online businesses related to the Recommender System were developed and the RS had been used more and more in marketing to enhance customer experiences and sales.

In the last few decades, many Recommender Systems (RS) have been created for a variety of applications like Jester [11] for funny content, the Bell Core Video Recommender [12] for films, and Ringo for music. This has also led to the establishment of many online businesses related to RSs [11] using them in marketing to improve customer experiences and increase sales [13]

Social networking sites (such as Facebook, Twitter, etc.) have emerged as a significant distribution channel for RS applications in the modern era. These well-known websites are widely regarded as the primary sources of data about individuals, making them an excellent choice to replace traditional techniques for recommendations with cutting-edge ones to increase accuracy [14] Thanks to contextual information like time, place, and people's feelings, these social networking sites open up a new channel for recommendations known as contextual recommender system.

It also presents a fantastic chance to give the recommendation a dynamic element [15] the seasonal marketing and conference suggestion are other areas where the context-aware recommendation is finding significant application [16]. The Intelligent Recommender System (IRS) uses statistical methods, artificial intelligence, and data mining techniques to be deployed and used as an intelligent bot. It can give students whether they are in high school or college, information about their academic performance and suggest the courses that are best for them. As a result, graduation rates increase as the failure rate of students who leave school in the middle of their studies decreases. José Aguilar and associates have proposed a general framework for an intelligent recommendation system based on knowledge-based recommendation systems.

The IRS's knowledge-based method recommendation stands out from other such methods in four distinctive ways: information acquisition, knowledge modeling, reasoning, and recommendation. Information acquisition is based on machine learning algorithms, while knowledge modeling involves identifying all the necessary information for making recommendations. Recommendation uses automatic inference abilities to make an inquiry, while reasoning verifies the thought process used to draw data from prior acquired knowledge (Fig. 1).

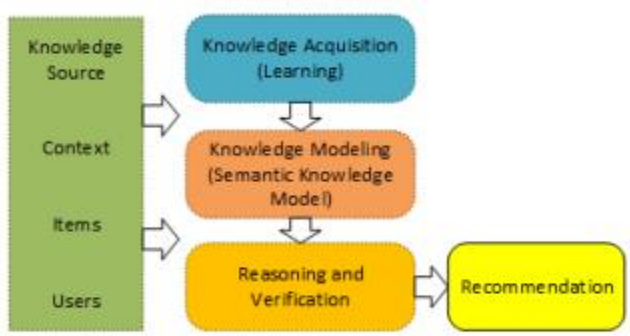

Fig 1. General architecture for intelligent recommendation systems.

The diagram below illustrates the structure of an Intelligent Recommender System (IRS) for college students.
To assess their performance, this proposal will take into account the students' academic records, test scores comparable to those from past courses, grades obtained per subject per semester, and their cumulative GPA from academic datasets. The results will then be utilized to predict graduation and academic success. Following this, the recommendation system will offer suggestions for the best course for students in order to further their academic achievements.

The diagram below demonstrates the design of an Intelligent Recommender System (IRS) specifically for college students. To evaluate them, this system will analyze their academic records and test results in comparison to former courses, their semesters' grades for each subject, and their overall GPA in available databases. This data will be evaluated to predict graduation and overall academic success. The IRS will further make recommendations on the most suitable subjects for the students according to their achievements.

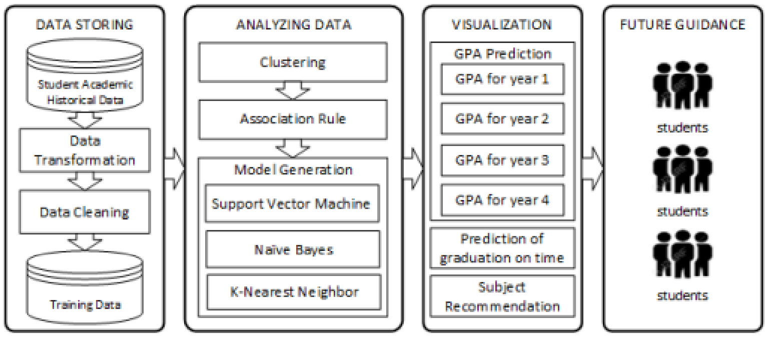

Fig 2. The proposed framework IRS for the college student.

3. Data storing

In this step, the information obtained from an academic database is prepared. The data is then reorganized after the data transformation stage in order to prepare it for processing by the next algorithm. The data are cleaned, the missing data are removed, the parameters used in the data analysis are noted, and the cleaned data are divided into training and test data.

3.1 Analyzing Data

In the data analysis stages, clustering techniques with the K-Means algorithm are used to classify data of similar objects based on prior academic success. From a machine learning perspective, the cluster corresponding to the hidden pattern and cluster search are categorized as learning without supervision. Additionally, based on the percentage of cases that were correctly predicted, the Association Rule was used to examine the relationship between the subgroup by identifying the traits that appeared on students the most frequently. The most common outputs will be examined and compared to clustering output in order to ensure more precise forecasts. Next, we evaluate the performance of three classifiers in the generation model: Support Vector Machine, Naive Bayes, and k-Nearest Neighbor. Afterward, the most efficient classifiers. Next, we evaluate the performance of three classifiers in the generation model: Support Vector Machine, Naive Bayes, and k-Nearest Neighbor. The best classifiers will then be used to predict and categorize academic achievement data, subject recommendations, and likelihood of graduating on time.

3.2 Visualization

When conducting a system analysis for an online recommender system, the first step is to understand how the current system functions. This helps us recognize any existing problems and identify whether the proposed system can address them or if we can improve upon the current one. System analysis is simply a process of examining a system, recognizing any issues, and coming up with solutions to fix them.

3.3 System Design

A system is a collection of interrelated units working together to achieve a goal. The creative process of the system design is the transformation of problem into solution. System design is the production of the system to be developed based on the content of the system design requirement. It can also be viewed as the process of analyzing what should be done and how it should be done. Thus, during the design of the proposed system, efforts were concentrated at producing design specifications that will result in a highly reliable system. Generally, a decision support system needs input to be passed into the system and the system needs to generate or produce an output. To operate, the system need access to stores or database whose content may need to change (update). The development system requires input data to be entered into it and this data are stored in a database to be used later for decision-making. The input, output as well as the database design for the decision support system is given below.

System design focuses on the technical and implementation concerns of the system. Few steps can simplify the task of designing coding of a system dramatically. The following steps were completed for designing the system. The role of the system is to provide an application bot that will be able to recommend or suggest to user different approach to solve problems relating to student frequently ask questions. This application will be simulating a typical case study of Lagos State University of Science and Technology (LASUSTECH). In this context of recommender system would allow student relationship with the institution. For accomplishing exploration of this study, the researcher adopted system development life circle as the methodology approach.

The Systems Development Life Cycle (SDLC) is a term used in systems engineering, academic advising systems and software engineering to describe a process for planning, creating, testing, and deploying an academic advising system.

4. Methodology

4.1 Personalized Intelligent Recommendation

One of the machine learning algorithms that is simple to use, effective, and well-liked is the Naive Bayes Algorithm (NBA). It has many advantages, such as a solid mathematical foundation, reliable classification accuracy, and little susceptibility to missing data. On probability theory, it is founded. A straightforward Bayesian classifier trained on recent exam data from the course to be read and taken can predict users' implicit sentiments toward reading books and be used to determine their current semester grade.

The naïve Bayesian algorithm's concept and method are as follows. The naïve Bayesian classifier uses the "attribute conditional independence hypothesis" to determine the class conditional probability P(Ci|a) assuming that sample an of class tag set C = C_i (i= 1, 2,..., n) has m attributes a_i (i= 1, 2,..., n).

$$P\left(C_i \mid a\right) = \frac{P(C_i)\,p(a \mid C_i)}{P(a)} = \frac{P(C_i)}{P(a)} \frac{m}{j=1} p(a_j \mid C_i)$$

By calculating conditional probabilities for each attribute and class prior probabilities based on the training dataset, a basic Bayesian classifier is trained. P (a_j | c_i).

A straightforward Bayesian approach is utilized to anticipate the implicit sentiment of the target user A1 on unrated books b5–b8 based on the user-sentiment matrix shown in Fig. 2. distinguish the implicit sentiment category. The emotions are categorized as "positive" and “negative” categories, and the set of category labels D = {D1 = positive, D2 = negative} The attribute x_j (j = 1, 2……, 8) indicates the sentiment towards book y_j, then the attribute value of user A5 in sample A1 is “negative” The implicit sentiment of the target user A1 on books b5-b8 is “positive,” “positive,” “positive,” “negative,” and “negative” by the plain Bayesian algorithm. “A1 has positive implicit sentiment towards books b5, b6, and b7, which means A1 has potential demand for these three books (Table 1).

Table 1: Different Recommendation Effect.

Range	Real	Predicted
1	1.1	6.9
2	3.5	5.4
3	2.5	7.3
4	4.5	9.3
5	1.9	7.4
6	5.1	6.2
7	5.2	9.9
8	6.1	10.5
9	6	8.9
10	5.5	8.4
11	2.9	4.6
12	5.2	6.9

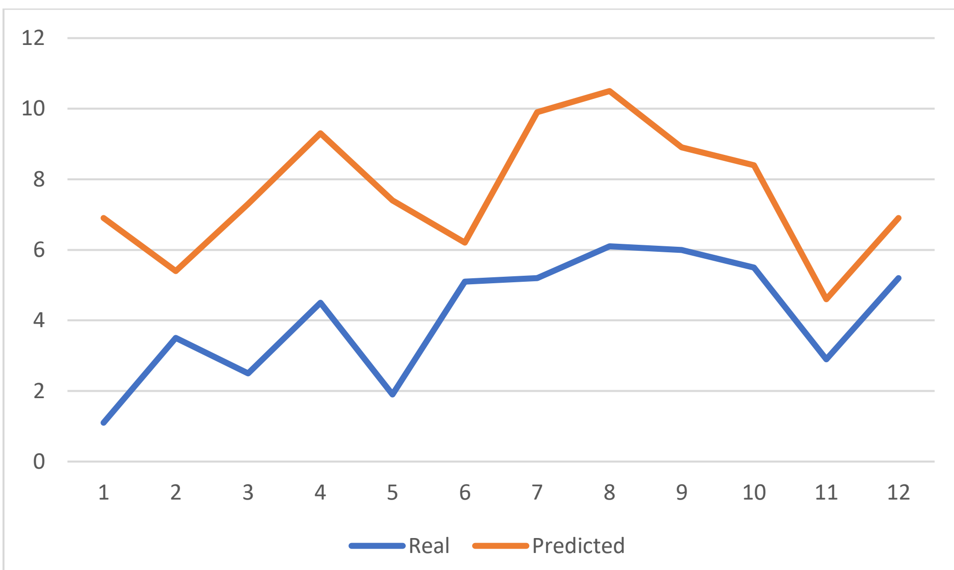

Fig. 3. Different recommendation effect.

4.2 Application Cases

This paper takes “course reading” as an example and proposes a personalized intelligent recommendation service for university students with the application of machine learning.

4.3 Book Reading Information

The recommended service's target audience is User A1, who is also the target user. Users A2-A5 are required to read some of the same literature as the target user A1 for the most recent exam. To determine the present requirements of the target user A1, the book reading data of users A2-A5 are examined. Fig. 3 displays the user ratings for each book, and since target user A1 did not read books b5–b8, the ratings for those books are denoted by "?". If the user's rating of the book is greater than or equal to 3, their sentiment toward it is labeled as "positive," otherwise, it is classified as "negative."

Table 2: User Reading Rating Matrix.

Range	Real	Predicted
1	1.1	1.9
2	3.5	3.4
3	2.5	3.3
4	4.5	7.3
5	1.9	6.4
6	5.1	6.2
7	5.2	1.9
8	6.1	9.5
9	6	8
10	5.5	8.4
11	2.9	4.6
12	5.2	6.9

The personalized intelligent book recommendation service considers users' explicit interests and potential needs by first extracting explicit user interests and making recommendations based on them, then using machine learning algorithms to explore implicit user emotions toward book resources, overcoming the lack of emotions, discovering current potential needs of users, and making recommendations based on them, and finally.

4.4 Personalized Interest Extraction

As seen in Fig. 3, the target user A1 expresses dominant sentiment towards books b1-b4. U1's sentiment towards books b1, b2, and b3 is positive, indicating that he has dominant interest in these three books, while U1's sentiment towards book b4 is negative, indicating his lack of interest in book b4, as shown in Table 2.

Table 3: Personalized Interest and Need of User Target.

Range	Real	Predicted
1	2.3	3.2
2	4.1	3.8
3	4.8	4.2
4	5.9	4.6
5	6.4	5.0
6	6.8	5,8
7	6.0	6.0

8	7.2	6.2
9	7.5	6.5
10	7.9	6.9
11	8.5	7.5
12	9.0	7.9

4.5 Personalized Intelligence Recommendation Result

Table 2 shows that the target audience has specific interests in books b1, b2, and b3. Collaborative filtering based on books yields three books, "New Data Structure Case Study," "Data Structure in Detail with Exercises (C Language Edition)," and "Discrete Mathematics and Its Applications," which are used as interest-based recommendation results. These three books are similar to books b1, b2, and b3. The books b5, b6, and b7 cater to the specific demands of the target audience. Mastering Data Science Algorithms, and Machine Learning: An Algorithmic Perspective are the first three books added to the recommendation section based on personalized demand for the target user A1. Second, using collaborative filtering, three books on algorithms and machine learning that are comparable to books b5, b6, and b7 were found. These books are "Python Algorithm Guide," "Algorithm Design and Analysis for Data Mining," and "Machine Learning Case Study," and they have also been added to the recommendation section based on the needs of individual users.

The recommendation list in Fig. 2 takes into account the user's personalized explicit interests as well as their implicit feelings about the book and only suggests books that will meet their current and future potential needs, which has led to high user satisfaction from the target audience.

User profiling can help libraries improve their services and resources, as seen in Fig. 4. Using customized reading as an example, the student can learn about the user's background, reading history, reading objectives, and behavior based on the user profile. The student can then actively customize the content for the user by displaying various reading resources for various users in order to satisfy the user's customized reading needs. The target user can be a second-year university student with the user profiles tags "sophomore," "computer major," etc. User profiles are updated as needed to reflect the evolving requirements and interests of users. To accommodate the dynamic changes in users' interests and demands, the content of personalized reading should also be altered and updated in accordance with the new user profiles.

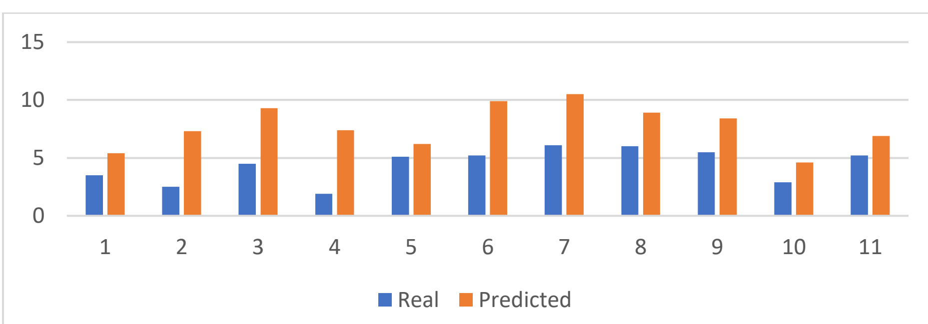

Fig. 4. Book reading information.

5. Conclusion

Academic advising holds a pivotal role in educational institutions, serving to help students navigate potential career directions, academic domains, and prospects within the college environment. Historically, this has been accomplished through in-person counseling by course advisors, guiding students on course selection, optimal timing, and strategies to attain higher levels of achievement. However, this traditional approach faces significant challenges in the present era, as contemporary students increasingly expect prompt and preemptive assistance, even in the absence of direct engagement. This preference stems from concerns about the unknown and a reluctance to share personal information due to privacy considerations.

This paper focuses on the utilization of a personalized recommendation system as the optimal method for enhancing and optimizing student performance. The system aims to provide users with automated relevant answers to their needs based on pre-informed data they have. This will be easily accessible through an institution's URL, every time they are on the portal. To support the system, both a user interface and a database will be developed to store relevant data for decision making. Additionally, a real-time database will be implemented to track requests, responses, keywords, logs, and feedback messages. Incorporating feedback from the initial deployment.

The application of machine learning technology is employed to create a personalized and intelligent recommendation service for students. A scheme based on machine learning is proposed, which involves traditional statistical analysis and collaborative filtering techniques to discover personalized explicit interests from user data. Furthermore, machine learning methods are utilized to identify users' current demands, analyze demand features, and analyze demand trends.

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