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A Rule-Based System for Admission Recommendations in Nigerian Tertiary Institutions

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ABSTRACT

This research presents a rule-based system to provide admission recommendations in Nigerian tertiary institutions. Unlike many existing studies that employ machine learning classifiers, this research aims to develop a transparent and deterministic system using predefined rules. The rule-based system recommends suitable courses based on candidates' O'level results, Unified Tertiary Matriculation Examination (UTME) scores, computed post-UTME scores, and specific eligibility criteria. By focusing on a rule-based approach, the system mitigates the limitations and potential misclassifications associated with machine learning, thereby enhancing the efficiency and accuracy of the admissions process. The methodology follows predefined guidelines to ensure a transparent and understandable admissions procedure. This approach avoids the complexities and uncertainties of predictive models, providing an accurate and reliable method for course recommendations. The rule-based recommendation system ultimately aims to support educational institutions and admission offices in making informed decisions regarding candidate qualifications, eligibility, and course recommendations.

1. Introduction

The demand for tertiary education in Nigeria has increased significantly over the years, providing the populace with essential skills and knowledge for the labor market. However, the university admission process is intricate and requires substantial time and effort to allocate courses to prospective applicants (Isma'il *et al*., 2020). The increasing number of students seeking enrollment adds complexity, necessitating a careful assessment of each candidate's profile to match program requirements. To establish a uniform standard for the placement of suitable candidates into universities, the federal government of Nigeria established JAMB in 1978 (Kennedy and Ebuwa, 2020). JAMB provides guidelines for admission to National Higher Institutions, detailing courses and entry requirements, such as "O" level credit passes and the minimum cut-off mark for the desired course of study in the Unified Tertiary Matriculation Examination (UTME) (Etaga *et al*., 2020). Candidates who meet these requirements may automatically be considered for admission.

Selecting a university course is a critical decision for both students and institutions. One major challenge in Nigerian tertiary institutions is the high student population, which strains educational facilities (Aduwa, 2020). This surge in demand significantly impacts the admission process, making it crucial to have a reliable and accurate system for selecting candidates who are likely to succeed academically (Mengash, 2020). Universities offer a diverse range of courses with varying entry criteria, which necessitates the development of a recommendation system that can match students' interests and qualifications with appropriate degree programs (Deraman *et al*., 2021).

A personalized recommendation system can assist both prospective students and the admissions office by suggesting courses that align with students' needs and capabilities (Ibrahim *et al*., 2018). Such systems address the issue of information overload, which can hinder users by increasing search time and the volume of retrieved information (Urdaneta-Ponte *et al*., 2021). In higher education, the teaching program is a fundamental objective and serves as a benchmark for institutional performance (Jacob & Ndayebom, 2022). Matching students with suitable courses is vital for academic success, as a student's performance often depends on their alignment with the course of study (Aliyu *et al*., 2021). Candidates may sometimes accept courses reluctantly due to competitive pressures or fear

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of missing out on admission, leading to poor academic outcomes.

It is important to recommend alternative study programs to candidates who do not meet the requirements for their first-choice courses or who apply for highly competitive programs. Often, institutions offer courses that are not closely related to the candidates' initial choices, and candidates may accept these offers out of necessity. This misalignment can negatively affect academic performance. Therefore, there is a need for a more reliable system to suggest courses based on candidates' qualifications and interests. An admission recommender system provides a solution by enabling institutions to match candidates with appropriate courses (Wakil *et al*., 2014). Such systems utilize advanced data analysis techniques to assist users in identifying items of interest by generating predicted likeliness scores or top-recommended lists. They analyze user data, extract relevant information, and forecast items to suggest to users (Ogunde & Ajibade, 2019).

In recent years, the adoption of machine learning and data mining techniques has expanded across various fields, with educational data mining gaining significant traction (Zabriskie *et al*., 2019). This research aims to improve the fairness, efficiency, and effectiveness of the admission process in Nigerian tertiary institutions. By leveraging a rule-based recommendation system, this study introduces a more inclusive and personalized approach to admissions, ensuring that deserving students have opportunities to pursue their desired courses while maintaining the integrity and standards of the educational institutions. Additionally, machine learning algorithms offer objectivity, reducing the likelihood of biased decisions based on subjective criteria. These systems provide transparency in decision-making, making it easier to understand how and why specific courses are recommended to students. Learning algorithms can also be adapted and updated to align with evolving educational goals and needs.

Originally developed by artificial intelligence researchers, rule-based systems often synonymous with expert systems rely on predefined rules to ensure transparency in the admission process (Masri *et al*., 2019). These systems help maintain fairness by assessing all candidates uniformly based on their profiles and course requirements, reducing the risk of discrimination based on factors such as gender, origin, or religion. While machine learning algorithms are effective in handling complex, variable data and can adapt to tasks without explicit rules (Bloch & Sacks, 2018), rule-based systems provide consistency and interpretability, making them ideal for tasks where transparency is essential.

This research developed a rule-based system for admission recommendations in Nigerian tertiary institutions. By utilizing predefined rules, the system offers a more precise and interpretable course recommendation process. The objectives of this study include defining admission rules, evaluating their effectiveness, generating course recommendations based on these rules, presenting the recommendation results, and performing system maintenance and updates as needed. The scope of this research covers data collected from The Federal University of Technology, Akure (FUTA), a public research university in Nigeria with a focus on technology and science-related disciplines. This study does not consider external factors that may influence admission decisions, such as socioeconomic status, interview performance, or additional entrance exams beyond O'level, UTME, and post-UTME that some institutions may require.

2. Recommendation System

Recommendation systems use a predictive machine model to provide personalized options to improve users' satisfaction. The admission recommender system provides the admission team with a way to find an appropriate course that best matches a candidate's qualifications and interests (Wakil *et al.*, 2014). A recommender system is a type of information filtering system that tries to suggest information items (books, movies, courses, etc.) that are likely to appeal to a user's preferences. They attempt to anticipate a user's rating or preference for a given item.Any information can be filtered using a recommender system and preferences set. Analyzing user data, extracting usable information, and lastly predicting items to users; are the approaches recommender systems employ to propose an item to a user (Ogunde & Ajibade, 2019).

Recommendation systems use algorithms to deliver product recommendations to users.Because of the advancement and popularity of artificial intelligence research, these systems have recently begun to incorporate machine learning techniques (Portugal *et al.*, 2018). Isma'il *et al.* (2020) was of the opinion that academics have recognized the enormous potential of recommender systems and have adapted them to predict courses, particularly for online course providers, such as Coursera, Lynda, and others. As a result, these technologies must be used in traditional colleges throughout admissions processes to assist students in selecting appropriate courses based on their capabilities. Recommendation systems implement various approaches. According to Gupta (2019), they are of different categories, Content-based systems, Collaborative Systems, and Hybrid Systems. He further explained that Content-based methods rely on two main sets of data to recommend items. The first piece of information is the item's specifications, while the second is the summaryof the user's choices. Keywords are associated with items based on the user's preferences. These methods recommend goods comparable to the user's previous or recent selections. Items are suggested by collaborative systems based on user and item similarity measures. Items that are recommended to a user are those popular among other users. The following are the three majorapproaches to combining collaborative and content-based filtering methods into a hybrid system:

i. Separate content-based and collaborative systems are implemented, with the outputs merged.

ii. In content-based methods, collaborative properties are used, and vice versa.

iii. A hybrid paradigm that incorporates both collaborative and content-based qualities.

2.1 Classifications of Recommender Methods

Al-Badarenah and Alsakran (2016) classified recommender methods into four general categories namely: Collaborative, Content-based, Knowledge-based, and hybrid recommender approaches.

i. Content-based recommender methods: Content-based recommender systems make recommendations to a target user based on similarities between the content of previously unseen items and the user's preferences (e.g., articles that the user has liked in the past).For example, the system may correlate the occurrences of keywords in a web page with the user's interest. The system analyzes the content of the items that the user has rated to generate a profile for the user based on the user's interests. When the user interacts with the recommender system later, the suggested products are comparable to those in the user's profile. Approaches such as approximation theory, machine learning, and various heuristics methods are applied for analyzing the items' content and finding regularities that can serve as a basis for making recommendations.

ii. Collaborative recommender methods: A collaborative recommender system makes suggestions to a target user based on similarities between the target user's past selectionsand those of other similar users. Collaborative systems predict items based on userevaluations rather than content analysis by machines. Users are typically grouped based on their preferences using approaches such as clustering. After creating clusters, those withthe strongest correlations with the target user are used to make suggestions. Analytical methods like correlation-based, Bayesian network and association rules techniques are commonly employed in collaborative recommender systems, which have gained attentionfrom academics and the industry.

iii. Knowledge-based recommender methods: When a recommender system offers recommendations based on particular queries rather than a user's rating history, it is known as a knowledge-based system. It may ask the user to provide a set of rules or guidelines on what the results should look like or an example of an item. The system then searches its item database for similar products and returns them (Wu, 2019).

iv. Rule-based recommendation systems: A rule-based recommendation system generates recommendations for users based on a set of predefined rules. These rules, created by domain experts or data analysts, are derived from patterns or heuristics found in the data. Rules typically have an "IF-THEN" structure, specifying conditions and recommended actions based on user preferences, item attributes, or other factors. When a user interacts with the system, their data is evaluated against the predefined rules to identify matches. The system executes actions specified in matching rules to generate recommendations.

v. Hybrid recommender methods: Hybrid recommender systems combine collaborative methods with content-based or knowledge-based approaches. They aim to improve recommendation accuracy while addressing drawbacks of traditional approaches (e.g., new item and new user problems).

2.2 Nigerian University Educational System

The Nigerian educational system comprises three phases of primary and secondary education. Six years of primary school, three years of junior secondary school, and three years of seniorsecondary school follow. The senior secondary education is assessed throughout the three years,with the final year evaluated by a national test administered by either WAEC or the Nigerian Examinations Council. The West African Senior Secondary School Certificate (WASSCE) or Senior School Certificate Examinations (SSCE), which replaced the former system of Ordinaryand Advanced Levels in 1989, will be awarded as a result (Ogunniran *et al.,* 2019).

For University admissions, credits in five important subjects in WASSCE or NECO, taken in no more than two sittings, are required for the admission process. Candidates must take the UTME after sitting for WASSCE or NECO. The national examination body, JAMB, administers the UTME. Following the UTME, various institutions conduct their post-UTME. Most universities expect a minimum UTME score of 200 out of 400 to participate in the post-UTME. The UTME and Post-UTME are the entrance examinations used to select students for university admission. Before being admitted, a candidate must succeed in WASSCE/NECO, UTME, and Post-UTME. University admissions are then based on departmental and faculty cut-off marks, considering the average scores in the UTME and post-UTME (Ogunniran *et al.,* 2019).

Education is the most powerful tool for improving a country's development and long-term viability. According to Asiyai and Okoro (2019), effective education plays a crucial role in fostering sustainable development by equipping individuals with the knowledge and skills needed to contribute meaningfully to society. They further emphasize that functional education focuses on the recipient's ability to apply what they have learned in real-world contexts. In the context of the Nigerian educational system, particularly the university admissions process, ensuring that students are matched with courses that align with their strengths and interests is essential for maximizing their potential contributions to socio-economic, technological, scientific, and political progress. Recommender systems can play a critical role in this process by analyzing academic profiles and preferences to guide students toward the most suitable courses of study, thereby enhancing the overall effectiveness of the educational system. By improving the alignment between students' abilities and their educational pathways, recommender systems not only contribute to individual success but also to national development by fostering a more competent and productive workforce.

The university admissions process is time-consuming and labor-intensive, involvesallocating courses to prospective students. The university education system is essential, especially for those who aspire to be researchers or preparing for a career. As a result, universityadmission is a concern. Every year, each institution undergoes several processes for accepting students who have applied for admission. The issue at hand is how candidates choose courses and how institutions assign available courses of study to them. It is a complicated issue influenced by criteria such as secondary school grades, UTME scores, and post-UTME scores, among others. Selecting and allocating an appropriate course of study for a given secondary school graduate can be a challenging decision for both students and universities. This process is not only based on the students' UTME scores, but also on their experiences, catchment areas, less educationally developed states, and various capacity weighting criteria that connect to their tertiary institution (Isma'il *et al*., 2020).

These challenges call for a need for recommender systems. Recommender systems can streamline and enhance the admissions process by efficiently matching students with courses based on their academic profiles, preferences, and other relevant criteria. These systems can analyze large datasets to provide personalized recommendations, thereby addressing the complexities involved in course selection and allocation. By doing so, recommender systems can reduce the time and effort required by both students and university administrators, ensure a more equitable distribution of educational opportunities, and ultimately improve the overall efficiency and fairness of the admissions process.

2.3 Related Works

Several recommendation systems have been developed to suggest courses for candidates. Ogunde and Ajibade (2019) provided a recommender system which employed advanced data analysis techniques. It helped users identify items of interest by creating a predicted likeliness score or a list of recommended items for each active user. Their research developed a collaborative filtering-based recommender system that dynamically recommends optional courses to undergraduate students based on their previous grades in relevant courses. They used a k-nearest neighbor approach to uncover hidden relationships between previous attended relevant courses and currently available elective courses. A dataset of real-world student results was used to build and test the recommendation model. The new systems would not only help students improve their academic performance but also reduce the workload of leveladvisers and school counselors.

Al-Badarenah and Alsakran (2016) proposed a collaborative recommender system that used courses taken by other students with comparable interests to recommend university elective courses to students. To detect patterns between courses, the proposed system used an association rules mining method as the foundation. Experiments were done with real datasets to examine the overall performance of the suggested approach. Aliyu *et al.* (2021) developed a new model to improve their previous work and address existing concerns.The catchment region, aggregate score from the UTME and post-UTME scores were used as parameters in the study. Multiple reference classifiers were trained and tested using the processed dataset of O'Level and JAMB results of candidates seeking admission to the University, generating the findings. Individual classifiers such as Logistic Regression, Naive Bayes, Decision Tree, K-Nearest Neighbor, and Random Forest were trained and evaluated using precision, recall, and f1-score as performance measures. The top-performing classifier, Random Forest, achieved 94.94% accuracy and correctly detected 94.17% of the classes.

Etaga *et al.* (2020) suggested a model to substantiate the degree of connection between candidates' UTME and Post-UTME results. Data was collected and evaluated using correlation analysis throughout a five-year period, from 2010 to 2014. Candidates' JAMB scores do not accurately reflect their genuine abilities or scores, according to the findings. There was a weak correlation between Candidates' JAMB scores and their corresponding PUTME results. According to the findings of the study, candidates' JAMB scores deviate from their equivalent PUTME values within the time period under consideration. As a check and balance, candidates who wish to go to college should keep the two exams in place.

Ragab *et al.* (2014) introduced a new hybrid recommender-based college admission system that used data mining techniques and knowledge discovery criteria. The suggested system achieved great performance by combining the efforts of two cascaded hybrid recommenders and a college predictor. For students in the preparatory year, the first recommender determined the students' tracks. The second recommender then places students who performed well in their preparatory year examinations into specialized institutions. For the purpose of forecasting the most likely colleges, the college predictor algorithm examines historical GPA student admissiondata from colleges. The system examines a student's academic achievements, background, records, and college admission requirements. The possibility that a student will enroll in a university or college was then predicted.

Wakil *et al.* (2014) introduced a new admission recommender system based on a hybrid Neural Network (NN), Decision Tree (DT), and Our Proposed Algorithm (OPA). They utilized DT to categorize the application into ten groups, each with its own set of characteristics, while NN was used to apply the applicant to the available courses; their method was combined with NN to discover the optimal course. As decision parameters, their system evaluates GPA, test score, candidates' interest, and desired occupations. The purpose of their research was to solve complex systems that used several criteria to apply multiple courses. Compared to other available admission methods, the system produced better and more reliable result; moreover, it could accurately match each candidate with appropriate course.

Semako (2021) recommended admissions procedures and top-notch instruction for institutions in Lagos State, Nigeria. He used descriptive survey and correlational research techniques, and developed research hypotheses. Using a sample size of 1187 and applying random, multi-stage, stratify, disproportionate, and purposeful sampling techniques, the study populationconsisted of 2623 academic staff members and 400-level students from three universities, one public and two privates, in Lagos State, Nigeria. Data was gathered using structured evaluation scales, the Admission Policy Scale (APS), and the Quality Teaching Questionnaire (QTQ). The test-retest technique was used to validate the instruments, and results showed that they were reliable with test-retest coefficients of 0.75 and 0.78 for each item, respectively.

Divakara Rao *et al.* (2023) proposed a machine learning-driven course recommendation system that uses the concepts of decision trees in machine learning to provide an effective method for making decisions and generating all the possible outcomes. The K-NN algorithm also helps to store all the available data, classifies a new data point based on the similarity, and produces the desired results. This project suggests appropriate learning courses for students by viewing their study streams and interests. Choosing the right learning pathway is essential for students to achieve their goals. However, the abundance of related information can make it difficult for students to select courses that align with both their interests and future demands. This proposed framework suggests courses previously taken by similarstudents, helping them choose a course of study based on their interest. The suggested method makes use of a number of data mining strategies to find correlations between courses. Evaluations based on analytical component are key aspects of the project's methodology. These methods enable the selection of a suitable course based on input, followed by recommendation for courses that meet various requirements. The outcome fulfills the requirements fordiscovering related courses and delivering them via cross-platform apps to for educational enhancement.

Ikono *et al*. (2017) investigated the pre-admission procedure used by the Nigerian university system to accept students. As a case study, they used Obafemi Awolowo University in Ile-Ife, Nigeria. They proposed a framework that groups students based on academic aptitude and strength. Their study aims to help stakeholders make wise choices on alternate course allocation. Okpa, Alade, Odigwe, and Sule (2020) used a descriptive survey study approach to examine the types of dishonesty that occur during the university admissions process and how it is handled. The sample consisted of 75 academic department heads and program administrators from two Nigerian public universities**.** The study was guided by four research questions. The 'Management of Dishonesty in students' Admission Questionnaire (MDSAQ) was developed, validated by professionals and used for data collection. Reliability was assessed using Cronbach's Alpha, yielding a score of 0.86, indicating strong reliability. With a criterion mean of 2.50, data were analyzed using mean scores and standard deviation. The results demonstrate the pervasiveness of dishonest behaviors in the student admissions process, including bribery, nepotism, racketeering, grade fraud, falsification of data, and manipulation of application criteria. Contributing factors included poor examination design, limited capacity, a high tendency for corruption, and weak enforcement of penalties. Adequate supervision and a shift in everyone involved in the admissions process' ethical focus are two suggested measures to stop the threat.

Joshi, Jadhav, Londase, and Nikat (2023) introduced a Career recommendation system aims to offer directionand assist students in selecting engineering streams with the help of a WebApp. The proposed WebApp aims to develop a system that suggest a course, based on certain fundamental information about the student such as academic performance, extracurricular activities, personal interests and aims. The WebApp mimics a career counselor by using a chatbot to interact with students and recommend engineering branches that align with their interests, utilizing machine learning for unbiased recommendations.

2.4 Research Gap

Several recommendation systems have been developed to recommend courses for candidates, but each has its limitations. Ogunde and Ajibade (2019) developed a recommender system focused on elective courses for current undergraduate students, utilizing collaborative filtering. However, their approach does not consider the needs of prospective students, leaving a gap in providing course recommendations for applicants prior to university admission. This study addresses this gap by developing a rule-based system aimed at recommending suitable courses of study to prospective undergraduate students based on their prior academic performances.

Al-Badarenah and Alsakran (2016) proposed a collaborative recommender system that relies on association rules mining. While effective in recommending elective courses to students with similar interests, their method does not consider the broader context of a candidate's overall academic profile, including standardized test scores and other relevant factors. This research fills this gap by incorporating multiple criteria, such as O'Level results and UTME scores, into a rule-based recommendation system. Aliyu *et al.* (2021) employed machine learning classifiers like Logistic Regression, Naive Bayes, Decision Tree, K-Nearest Neighbor, and Random Forest for course recommendations. While these classifiers were effective, they pose a risk of misclassification, which can lead to unsuitable course recommendations. This study addresses this issue by using a rule-based system that relies on predefined decision rules derived from students' academic performance, reducing the risk of misclassification.

Etaga *et al*. (2020) focused on the correlation between UTME and Post-UTME scores, finding a weak correlation between them. While their research highlights the inadequacy of using only UTME scores for admissions, it does not propose a solution for better course allocation. This study builds on their findings by incorporating multiple academic criteria into a rule-based system that offers more accurate course recommendations. Ragab *et al.* (2014) introduced a hybrid recommender system combining data mining techniques for college admission predictions. However, their approach primarily targets students already in the preparatory year, rather than prospective students. This research fills this gap by focusing on course recommendations for candidates before they enter the university system.

Wakil *et al.* (2014) developed a hybrid recommendation system using Neural Networks, Decision Trees, and a proposed algorithm. While effective, their system's complexity may not be suitable for all educational contexts. This study offers a simpler, rule-based approach that can be easily adapted and applied to different educational institutions. Semako (2021) recommended admissions procedures based on descriptive and correlational research but did not propose a specific recommendation system for course allocation. This research addresses this by developing a rule-based system that provides tailored course recommendations to prospective students.

Divakara Rao *et al.* (2023) proposed a machine learning-driven course recommendation system focusing on decision trees and K-NN algorithms. While effective in suggesting courses, their system does not fully address the challenge of aligning recommendations with a student's overall academic background. This study overcomes this by using a rule-based approach that considers multiple academic factors to provide more accurate recommendations. Ikono *et al.* (2017) explored the pre-admission procedures in Nigerian universities and proposed a framework for grouping students based on academic aptitude. However, their work does not extend to course recommendation based on specific criteria. This study builds on their framework by incorporating a rule-based system that recommends courses based on students' academic strengths and interests.

Okpa *et al*. (2020) highlighted the issue of dishonesty in the admissions process but did not propose a solution for improving course recommendation accuracy. This research addresses this gap by developing a transparent, rule-based recommendation system that relies on verifiable academic data. Joshi *et al.* (2023) introduced a career recommendation WebApp for engineering streams, but their focus is limited to a specific field and does not generalize to broader academic contexts. This study expands the scope by offering a rule-based recommendation system applicable to various courses of study across different disciplines.

3. Methodology

The research utilized the Python programming language, a high-level, general-purpose language known for its ease of use. Exploratory data analysis and data visualization played a vital role in this research. The Matplotlib and Seaborn libraries, both tailored for Python, were used for data visualization and plotting.

3.1 The conventional admission process

Nigerian universities offer admission to prospective students through a process that is regulated by the Joint Admissions and Matriculation Board (JAMB) and individual universities. Prospective students seeking admission to Nigerian universities must take the Unified Tertiary Matriculation Examination (UTME) administered by JAMB. The UTME is a standardized exam assessing candidates' knowledge and aptitude across various subjects. The results of the UTME are used as a primary basis for admission consideration. After the UTME, each candidate receives a UTME score based on their performance in the examination. JAMB sets a general cutoff mark as an admission benchmark for tertiary institutions**.** Some Nigerian institutions, in addition to the benchmark set by JAMB, specify the O'Level subject combinations and minimum UTME score requirements for each course they offer. Prospective students must meet these requirements to be eligible for admission consideration.

After the UTME, universities conduct a Post-UTME screening exercise. The screening process may include a written test, oral interview, and/or other assessments, depending on the university's policy. The purpose of the screening is to further evaluate candidates' suitability for the chosen course. Post-UTME scores are typically combined with UTME scores to calculate a candidate's overall score. Nigerian universities set admission cut-off marks, which represent the minimum scores required for admission into various courses. Cut-off marks are determined by factors such as course competitiveness, candidate performance, and available slots. Candidates who meet or exceed the cut-off marks have a higher chance of being offered admission.

Universities identify some applicants who do not meet the minimum requirements (such as UTME score, subject combinations, or cutoff marks) for their applied course. The applicant's profile, academic performance, and available vacancies in other courses are checked. They consider alternative courses that the applicant may be eligible for based on their qualifications and subject combinations. They match eligible applicants with these courses. Alternative course selection typically depends on the applicant's UTME score, subject combinations, cut-off marks, and slot availability. Universities prepare a merit list based on the overall scores of candidates. The merit list includes candidates who have achieved the highest scores and meet the admission requirements. In addition to the merit list, Nigerian universities also implement a quota system, which allocates a certain percentage of admission slots to candidates from disadvantaged states and other categories.

It's important to note that specific admission processes may vary among Nigerian universities. The procedures outlined above represent a general framework for how Nigerian universities offer admission to prospective students. Candidates are always advised to refer to the official websites and admission guidelines of the universities they are interested in for detailed and up-to-date information about the specific admission process for each institution.

3.2 The proposed system

The proposed system is a rule-based admission recommendation system designed to automate the admission recommendation process and assist universities in suggesting alternative coursesfor applicants who do not meet the requirements of their chosen course. The system involves acquiring knowledge about the university's course offerings and the applicant's qualifications. A recommendation function generates course suggestions based on predefined rules. Recommendations consider the applicant's UTME score, subject combinations, and cutoff marks. The output includes:

i. The candidate's preferred course provided they meet the requirements.

ii. A list of recommended alternative courses, sorted based on qualifications, provided whenthe candidate does not meet the requirements

iii. Reasons for not meeting the requirements. This is only provided for candidates who donot meet the requirements.

The system would be executed for all applicants, taking into account university policies and regularly updating to align with changes. This system optimizes the admission process, improvingthe chances of offering admissions to deserving candidates. The framework and methodology of the proposed approach is presented in Figure 1.

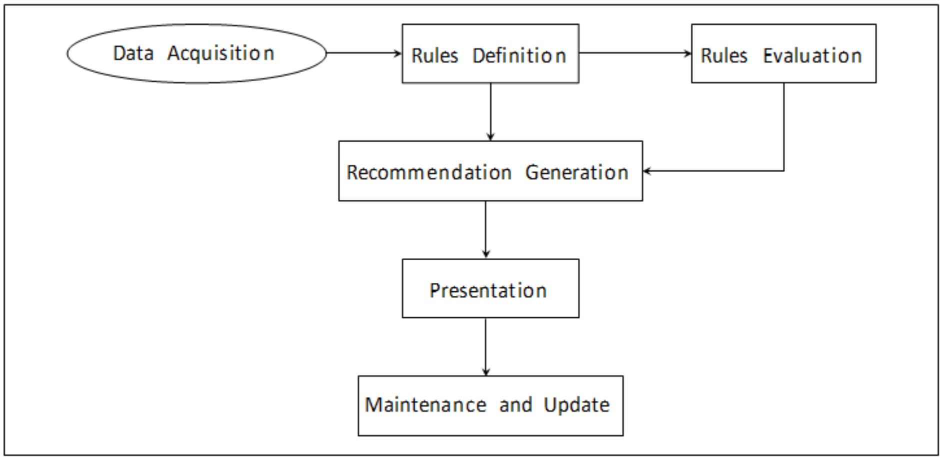

Figure 1: Conceptual framework of the recommendation system

3.3 Data acquisition and description

This phase of the rule-based admission recommendation system involves the collection and preparation of data to develop the recommendation system. The data utilized in this research was sourced from the admission office of the Federal University of Technology, Akure (FUTA). The dataset comprised various features, including the candidates' UTME registration number, gender, state of origin, faculty, UTME score, post-UTME score, SSCE results, and their chosen course. The acquired student data undergoes preprocessing steps to ensure its quality and compatibility.This involves handling missing values and performing necessary data transformations. The Data Acquisition phase lays the groundwork for the rule-based recommendation system, providing a comprehensive dataset. This data forms the basis for the subsequent stages of the recommendation system, including rule development, course matching, and final course recommendations.

3.4 Rules Definition

The goal of the system is to automate the admission recommendation process for prospective students based on their academic qualifications and the admission requirements of different courses. The phase involves formulating and implementing rules that determine the eligibilityof students for specific courses; it describes the rules formulated as code and provides relevant information on the implementation. The Rules Definition phase plays a crucial role in the admission recommendation system asit establishes the criteria for course eligibility and qualification. This phase involves defining the requirements, subject combinations, grade point values, and cutoff scores for each course. The following were formulated as rules:

3.4.1 O'Level requirements

The admission requirements for each course were defined as shown in Table 1, specifying the compulsory and optional O'Level subjects. The O'Level course requirements dictionary was formulated, containing the necessary information for each course, such as compulsory O'Level subjects, the number of optional subjects required, and the available options.

Table 1 O'Level Requirements

Course	Compulsory Subjects	Optional Subjects

COMPUTER SCIENCE	English Language, Mathematics, Physics, Chemistry	Biology, Agricultural Science (1 option)
ARCHITECTURE	English Language, Mathematics, Physics	Chemistry, Geography, Fine Art, Technical Drawing, Economics (2 options)
ESTATE MANAGEMENT	English Language, Mathematics, Economics, Physics	Geography, Agricultural Science, Biology, Chemistry, Technical Drawing, Government, History (2 options)
MINING ENGINEERING	English Language, Mathematics, Physics, Chemistry	Further Mathematics, Economics, Geography, Biology, Agricultural Science, Civic Education, Data Processing, Computer Studies, Animal Husbandry (1 option)

Source: https://futa.edu.ng

Table 1 presents the O'Level requirements for selected courses, which are part of an extensive list of courses. The O'Level requirements define the compulsory and optional subjects needed for admission into each course. For each course, the 'Compulsory Subjects' column lists the subjects that must be taken and passed at the O'Level examination.

These subjects are essential and non-negotiable for admission. The subjects may include English Language, Mathematics, and specific subjects related to the course, such as Biology, Chemistry, Physics, Economics, Geography, etc. The 'Optional Subjects' column indicates the number of optional subjects that students can choose from a given set of options. These optional subjects provide flexibility for students to showcase their interests and strengths. The options listed under the 'Options' column represent the available subjects from which students could select the required number of subjects. By adhering to the specified O'Level requirements, prospective students can fulfill the prerequisites necessary for admission into their desired courses. These requirements ensure that students possess the foundational knowledge and skills relevant to their chosen field of study.

3.4.2 UTME subject combinations

The UTME subject combinations required for each course were also defined as gotten from FUTA official website. The UTME combinations dictionary was created, consisting of compulsory and alternative subjects that a candidate could choose.

Table 2 UTME Subject Combinations

Course	Compulsory Subjects	Alternative Subjects	Count
MICROBIOLOGY	ENG, BIO, CHE	MTH, PHY	1
ARCHITECTURE	ENG, MAT, PHY	CHE, GEO, TED	1
ESTATE MANAGEMENT	ENG, MAT, ECO	GEO, CHE, GOV, AGR, BIO, TED, HIS	1

MINING ENGINEERING	ENG, CHE, MAT, PHY	-	0
ANIMAL PRODUCTION AND HEALTH SERVICES	ENG, CHE	MTH, PHY, BIO, AGR	2
CIVIL AND ENVIRONMENTAL ENGINEERING	ENG, CHE, MAT, PHY	-	0

Source: https://futa.edu.ng

Table 2 presents the UTME requirements for specific courses as defined in the code. It outlines the compulsory subjects and alternative subjects for each course, along with the count of alternative subjects allowed. For example, in the course of MICROBIOLOGY, the compulsory subjects are English Language (ENG), Biology (BIO), and Chemistry (CHE). The student has the option to choose either Mathematics (MTH) or Physics (PHY) as an alternative subject, only one alternative subject is allowed. Similarly, for the course of ARCHITECTURE, the compulsorysubjects are English Language (ENG), Mathematics (MAT), and Physics (PHY), with Chemistry(CHE), Geography (GEO), and Technical Drawing (TED) as alternative subjects; only one alternative subject is allowed. This table outlines the specific UTME subject combinations that candidates must fulfill for each course, ensuring they meet the admission requirements.

3.4.3 Assumed grade point values

The grade point values for different grades were assumed and established to assess the performanceof students in O-level subjects. The grade point values dictionary assigns numerical values to different grades; tertiary institutions could set these values based on their specific need and policies.

Table 3 Grade point values

Grade	Grade Point Value
A1	4.0
B2	3.6
B3	3.2
C4	2.8
C5	2.4
C6	2.0
0	NaN

In Table 3, the “Grade” column represents the different grades, and the “Grade Point Value” column represents the corresponding grade point values assigned to each grade. The grade point values are used to quantify the performance of students in a numerical form.

A critical aspect of this definition is to establish rules for handling unaccounted grades,such as F9 and E8, which are not explicitly captured in the grade point values dictionary. The unaccounted grades are treated as missing values (NaN). The unaccounted grades such as F9 andE8 were not considered as pass grades. They were treated as zero in terms of their contribution to the O’Level score. In the context of the recommendation system, this implies that these grades are considered as non-passing grades or grades with no point value assigned to them.

3.4.4 Assumed weightings

Weightings were assumed and assigned to UTME and Post-UTME scores based on the competitiveness of courses, in order to calculate the weighted score for each student. Tertiary institutions could set these values based on their policies. The course weights dictionary specifiesthe weightings for each course as shown in Table 4.

Table 4 Course Weight Points

Course	UTME Weight	Post-UTME Weight
MICROBIOLOGY	0.6	0.4
ARCHITECTURE	0.5	0.5
ESTATE MANAGEMENT	0.6	0.4
MINING ENGINEERING	0.5	0.5
ANIMAL PRODUCTION AND HEALTH SERVICES	0.6	0.4
ELECTRICAL AND ELECTRONICS ENGINEERING	0.6	0.4

By assigning different weightings to the UTME and Post-UTME scores for each course, the system can calculate a weighted score that reflects the relative importance of these two examination results in determining qualification for a particular course. The course weights dictionary is used in a function to calculate the weighted score based on the student's UTMEand Post-UTME scores, which is then compared to the threshold score required for qualification in the recommendation function. The weighted score is calculated by multiplying the UTME score with its corresponding weightand the Post-UTME score with its corresponding weight. The results of these multiplicationsare then summed together to obtain the final weighted score. Overall, the course weights dictionary allows for flexibility in adjusting the impact of UTME and Post-UTME scores on the qualification process for different courses, based on the specific requirements and preferences ofthe educational institution or program.

3.4.5 Assumed cutoff scores

Cutoff scores were defined for each course based on their competitiveness, determining the minimum required weighted score for admission. Tertiary institutions are at liberty to set these values based on their policies. The course cutoffs dictionary stores the cutoff scores for differentcourses as shown in Table 5.

Table 5 Course Cutoff Scores

Course	Cutoff Score
MICROBIOLOGY	65
ARCHITECTURE	75
ESTATE MANAGEMENT	70
MINING ENGINEERING	80
ANIMAL PRODUCTION AND HEALTH SERVICES	60

ELECTRICAL AND ELECTRONICS ENGINEERING	80

The weighted score of an applicant is compared with the course cutoff score for their desired program. If the weighted score meets or exceeds the cutoff score, the applicant meets the minimum requirement for admission. Conversely, if the weighted score falls below the cutoff score, the applicant may not be considered for admission. The relationship between the weighted score and course cutoffs is crucial in the admission recommendation process.

3.4.6 Implementation of rules

The formulated rules described above were implemented in the system using Python codes. Functions such as check combinations and calculate score evaluate the students' qualifications and determine their eligibility for specific courses based on the defined rules.

i. Compulsory O-level Subjects: Checks if the student meets the required O-level subjects for the applied course.
ii. UTME Subject Combination Requirements: Verifies if the student's UTME subject combination meets the requirements for the applied course.
iii. Missing Compulsory Subjects: Determines if the student is missing any compulsory subjects required for a course.
iv. Insufficient Optional Subjects: Checks if the student has an insufficient number of optional subjects for a course.
v. Weighted Score Requirement: Compares the student's weighted score with the cutoff score for the applied course.

These rules collectively form the backbone of the rule-based admission recommendation system, enabling the system to assess each applicant's eligibility for specific courses based on their academic qualifications and institutional requirements.

3.4.7 Algorithm for the Rule-Based Recommendation System

The algorithm used for the rule-based recommendation system is outlined below.

i. Define the course requirements, UTME combinations, grade point values, course weights, course cutoffs, and school department dictionary
ii. Define a function, `check_combinations(row, course)`, to check if a student's UTME subject combination meets the requirements for a given course. This function checks the compulsory and optional subjects, as well as the total number of subjects.
iii. Define a function, `calculate_score(row, reqs, opts, course)`, to calculate the weighted score for a student applying for a course. This function checks if the student has the required subjects and optional subjects, calculates the weighted score using UTME and Post-UTME scores, and determines if the student qualifies for the applied course based on the cutoff score.
iv. Define a function, `check_olevel_requirements(row, course)`, to check if a student meets the compulsory O-level requirements for a course. This function checks if the student has the required subjects and optional subjects with valid grades.
v. Define the main function, `recommend_courses(df, output_file)`, which takes a DataFrame `df` containing student data and an output file name. This function iterates over each student in the DataFrame and performs the following steps:
    i. Check if the student applied for a valid course. If not, add a corresponding entry in the output data.

ii. Check if the student meets the compulsory O-level requirements for the applied course. If not, add a corresponding entry in the output data.
iii. Check if the student meets the UTME combination requirements for the applied course. If not, add a corresponding entry in the output data.
iv. Calculate the weighted score for the applied course and add it to the recommendations list.
v. Check if the student qualifies for any course within the same school. If so, calculate the weighted score for each course and add them to the recommendations list.
vi. Check if the student qualifies for any course in other schools. If so, calculate the weighted score for each course and add them to the recommendations list.
vii. Sort the recommendations based on the weighted score in descending order.
viii. If the student qualifies for the applied course or any recommended course, add a corresponding entry in the output data.
ix. If the student does not qualify for the applied course and there are no recommendations, add a corresponding entry in the output data.
x. If the student does not qualify for the applied course but there are recommendations, add a corresponding entry in the output data.

vi. Create a DataFrame `df_output` from the output data and save it to the specified output file. Call the `recommend_courses` function with the provided DataFrame `df` and the output file name `'recommended_courses.csv'`.

This algorithm outlines the steps involved in evaluating each student's qualifications anddetermining their eligibility for specific courses based on defined rules and criteria.

3.5 Rule evaluation

The evaluation and monitoring phase of the rule-based admission recommendation system playsa crucial role in assessing the eligibility of students and monitoring their progress throughout the admission recommendation process. This phase involves the evaluation of various factors, such as course requirements, subject combinations, weighted scores, and cutoffs, to determine whether a student qualifies for a particular course or not.

3.5.1 Evaluation c riteria process

The evaluation criteria encompass various aspects of student qualifications, including:

I. O'Level Requirements: The system evaluates whether the student has the required O'Level subjects (both compulsory and optional) with valid grades as defined in Table 1.
II. UTME Subject Combinations: It evaluates the student's UTME subject combination meets the specified requirements for the desired course. This evaluation is based on the data presented in Table 2.
III. Weighted Score Calculation: The system calculates and evaluates the weighted score for each student based on their UTME and Post-UTME scores, applying the weightings defined in Table 4.
IV. Comparison with Cutoff Scores: The calculated weighted score is compared against the cutoff scores (Table 5) to determine if the student meets the minimum requirement foradmission.

These evaluation processes ensure that only students who meet the stipulated academic standards and criteria are recommended for admission into their chosen courses. The systematic evaluationof rules ensures transparency and fairness in the admission process, providing clear guidelines for decision-making.

4. Results and Discussions

4.1 Recommendation generation

In this phase, the system generates recommendations for courses based on the eligibility criteriaand the student's profile. The result of the recommendation system is shown in Table 6. The recommendation system generates the results as an Excel file, which ensures ease of access and allows the admission team to perform any additional processing as needed by the institution.

Table 6: Recommendation Result

	Registration Number	Course Applied	Qualified	Reason for disqualification	Recommended Course(s)
0	86978854DE	ARCHITECTURE	Yes	-	ARCHITECTURE
1	86073283GI	MICROBIOLOGY	Yes	-	MICROBIOLOGY
2	86978854DE	ARCHITECTURE	Yes	-	ARCHITECTURE
3	86572232CI	ESTATE MANAGEMENT	No	Did not meet compulsory O-level requirements	No Course recommended
4	85336138JH	MICROBIOLOGY	No	Did not qualify for the course	HUMAN ANATOMY, PHYSIOLOGY
5	85773478AC	MINING ENGINEERING	No	Did not qualify for the course	MARINE SCIENCE AND TECHNOLOGY, BIOLOGY(STORAGE...
6	86049311BA	ANIMAL PRODUCTION AND HEALTH SERVICES	No	Did not meet UTME subject combination requirem...	No Course recommended
7	86072867FF	ELECTRICAL AND ELECTRONICS ENGINEERING	Yes	-	ELECTRICAL AND ELECTRONICS ENGINEERING
8	86704590HC	CIVIL AND ENVIRONMENTAL ENGINEERING	No	Did not qualify for the course	MARINE SCIENCE AND TECHNOLOGY, BIOLOGY(STORAGE...
9	86674455HD	MECHANICAL ENGINEERING	Yes	-	MECHANICAL ENGINEERING
10	86460677ED	FOOD SCIENCE AND TECHNOLOGY	Yes	-	FOOD SCIENCE AND TECHNOLOGY
11	85984153CJ	QUANTITY SURVEYING	No	Did not meet compulsory O-level requirements	No Course recommended
12	86815620IA	CIVIL AND ENVIRONMENTAL ENGINEERING	Yes	-	CIVIL AND ENVIRONMENTAL ENGINEERING
13	86063819DJ	URBAN AND REGIONAL PLANNING	Yes	-	URBAN AND REGIONAL PLANNING
14	85755878DE	MECHANICAL ENGINEERING	No	Did not qualify for the course	COMPUTER SCIENCE, MARINE SCIENCE AND TECHNOLOG...

The admission recommendation system was implemented to assist the admission office inmaking informed decisions regarding the admission of applicants. The system evaluated the qualifications of each applicant based on their registration number, course applied, qualificationstatus, reason for disqualification (if applicable), and recommended course(s) (if qualified). A total of 4512 applicants were evaluated using the system. Among the applicants, 1878 were considered qualified for their respective courses, 1283 were recommended alternative courses, while 1351 were disqualified.

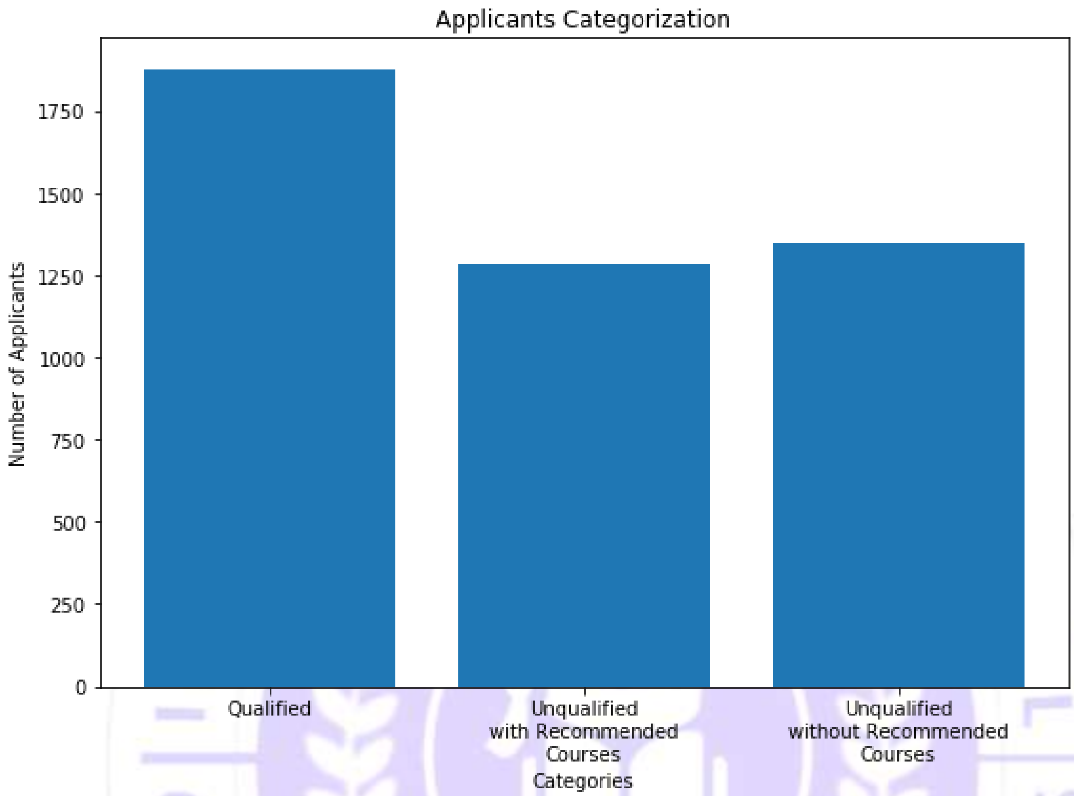

Figure 2: Applicant categorization

A bar chart representation of the categorization of the result is presented in Figure 2. For the qualified applicants, no further analysis or changes were made to their course selection, and they were recommended to pursue the course they originally applied for. This indicates that their qualifications met the requirements for their desired courses, and no alternative course recommendations were necessary. On the other hand, the disqualified applicants did not meet certain criteria for their chosen courses. The reasons for disqualification varied, including not meeting compulsory O-level requirements, failing to meet UTME subject combination requirements, and not qualifying for the chosen course based on their qualifications. As a result, no course recommendations were provided for these applicants.

It is worth knowing that the rules and requirements of the recommendation system could be modified to suit the needs of various educational institutions for their admission process. Therecommendation system generates the results in the form of an Excel file, providing convenient accessibility and seamless integration into existing workflows.

4.2 Presentation

In the presentation phase, the results of the evaluation and recommendation process are communicated to the stakeholders, including admission officers and academic advisors. This phase is critical for ensuring that the insights derived from the recommendation system are clearly and effectively conveyed to support informed decision-making. The system generates detailed reports that provide a comprehensive overview of each student's qualifications, eligibility status, and recommended courses.

The reports are designed to be user-friendly and accessible, often presented in the formof Excel files. This format not only facilitates ease of access and data manipulation but also integrates seamlessly with existing administrative systems used by educational institutions. The Excel reports enable stakeholders to perform additional analyses, customize views, and extract specific data points relevant to their needs. Furthermore, the reports highlight key metrics and insights, such as weighted scores, cutoff comparisons, and subject-specific performance, allowing admission officers to quickly assess each candidate's suitability for various courses. By presenting the data in a structured and visual format, the system aids in identifying trends, making comparisons, and ensuring transparency in the admission process.

Overall, the presentation phase transforms the raw data and computational results into actionable intelligence, supporting a data-driven approach to student admissions. By leveraging the clarity and flexibility of the Excel format, the system ensures that all stakeholders can effectively engage with the data, fostering a collaborative and efficient admission process.

4.3 Maintenance and update

The maintenance and update phase is integral to ensuring the ongoing accuracy, relevance, and efficiency of the rule-based admission recommendation system. This phase involves a systematic approach to periodically review and update the various components of the system to align with changing academic standards, admission policies, and industry requirements. Regular updates to the course requirements, UTME subject combinations, weighted scores, and cutoff values are essential to reflect the latest criteria set by the institution and regulatory bodies. These updates ensure that the recommendations provided by the system remain pertinent and accurate, thereby maintaining the trust and reliability placed in the system by stakeholders.In addition to content updates, this phase also addresses the technical maintenance of the system. This includes routine checks and optimizations of the system's infrastructure to enhance performance and resolve any issues or bugs that may arise. Ensuring robust system performance is crucial for handling large datasets efficiently and providing timely recommendations.

User feedback plays a pivotal role in the maintenance and update phase. By collectingand analyzing feedback from admission officers, academic advisors, and other stakeholders, thesystem can be continually refined and improved. This feedback loop helps identify potential areas for enhancement, whether in terms of user interface improvements, new features, or adjustment to existing functionalities. Moreover, this phase involves ensuring the security and integrity of the data processedby the system. Implementing stringent data protection measures safeguards the privacy and confidentiality of student information, which is paramount in maintaining compliance with data protection regulations and building stakeholder confidence. By incorporating regular maintenance and updates, the rule-based admission recommendation system remains a dynamic and adaptive tool that evolves in tandem with the educationallandscape. This ongoing process supports the system's longevity and effectiveness, ultimately contributing to a streamlined and data-driven admission process.

5 Conclusion

In conclusion, this paper has presented a comprehensive framework for a rule-based admission recommendation system tailored to educational institutions. By leveraging data-driven rules, the system effectively automates the evaluation of student qualifications against course requirements, enhancing the efficiency and objectivity of the admission process. The study highlighted the pivotal phases of data acquisition, rules definition, recommendation generation, presentation, and maintenance. Each phase contributes uniquely to the system's functionality, ensuring that it not only meets current admission standards but also adapts to evolving educational policies and institutional needs. Key findings underscored the system's capability to generate accurate course recommendations based on student profiles, thereby supporting informed decision-making by admission officers and advisors. The Excel format output facilitated ease of access and additional processing, catering to the diverse operational requirements of educational institutions.

Looking forward, future research could explore enhancements in algorithmic efficiency,scalability across diverse educational contexts, and integration with emerging technologies. These advancements promise to further optimize the admission process, offering personalized recommendations while maintaining transparency and fairness. In essence, the presented system represents a significant step towards enhancing the admission process's efficacy, ensuring equitable opportunities for prospective students while supporting the strategic goals of educational institutions.

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