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A Review of Intelligent Study Recommendation Systems Based on Student Performance

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Abstract

By forecasting student performance and improving study strategies, intelligent study suggestion systems have been developed to improve academic success as educational data becomes more widely available and the need for customized learning experiences increases. These recommendation systems use cutting-edge fields of DM, ML, AI, and data on education analytics to identify variations in student behaviors, academic performance, and engagement levels. After analyzing these parameters, the intelligent recommendation system renders assistance in the mastery of concepts, academic stress, course selection, and many other ways to bridge areas in need of support like lack of personal guidance, ill-fitted from a one-size-fits-all method, or learning gaps in large classrooms. Recent studies from 2021-2025 have evidenced how effective approaches ranging from deep learning model implementations, reinforcement learning frameworks, and hybrid multi-criteria systems to ensemble techniques such as RF give superlative prediction accuracy and adaptability. While these systems hold the promise of personalizing learning pathways and optimizing education-oriented resources, limitations can be observed in terms of data dependence, black-box model interpretability, and scalability with respect to different academic contexts. This review analyzes and compared several approaches studied in the recent literature, highlighting various methods, datasets, and results, stressing the shortcomings of each approach, gaps, and future work in integrating multimodal sources of data, hybrid architectures (symbolic-neural), and adaptive feedback evolving with student progress. The work substantiates intelligent recommendation systems as a basis for the conversion of classical education into a personalized and data-driven learning environment for sustainability.

Keywords: Artificial Intelligence (AI), Machine Learning, Improved Learning, Course Recommendation System, Personalized Learning, Student Performance Prediction, Learning Analytics, Recommender System in Education.

1. Introduction

Historically, the Education system highlights the rich tradition of learning and knowledge in the Universe. However, the ''Gurukula'' system in ancient days was famous for its all-time access to teachers and abundant knowledge resources with students, living on the premises to pursue their education. Nalanda University, Takshashila was the maiden university in India, which was started in the 5th Century BC. At this time the new teaching (classroom) method was introduced. This type of learning education was limited and did not have exposure across the world. Over the centuries, the education system has continued to evolve and adapt to changing times with a wide range of educational institutions offering diverse courses and programs [4]. E-learning is currently outperforming conventional educational institutions.

The field of education is undergoing significant transformation thanks to the implementation of AI technologies and data-driven tools, with one of the most exciting advancements being the introduction of intelligent study recommendation systems. Traditional education methods assume that all students learn at the same pace; in reality, students face different problems, including missing important concepts, dealing with stress, or lacking personal tutoring opportunities in large classrooms [5], [19]. Hence, there is a need for personalized support, and intelligent recommendation systems come in to fill that role by using student performance data to detect learning areas and recommend strategies and resources for study that are specifically tailored.

These systems have the capability to predict student performance, create customized interventions, and even avert dropouts by identifying at-risk learners early through the application of AI, ML, and educational DM [2], [6]. Studies have explored various methods, including reinforcement learning applied to tailored scheduling assessments [2].

From the outset, such mobile applications allow students to obtain early feedback and customized strategies for learning. Although they try to make decisions better for academic objectives, make the process more personal, and reduce stress, there are problems with datasets that are smaller, the scalability, and the interpretability of complex models [30], [38]. Therefore, today, research tries to build systems that are even more adaptive, explainable, and scalable, which can continuously learn from new data and help students in various educational environments [10], [11]. In general, intelligent study recommendation systems represent a very strong step to personalized learning, considered efficient, and sustainable for the future.

2. Background Theory

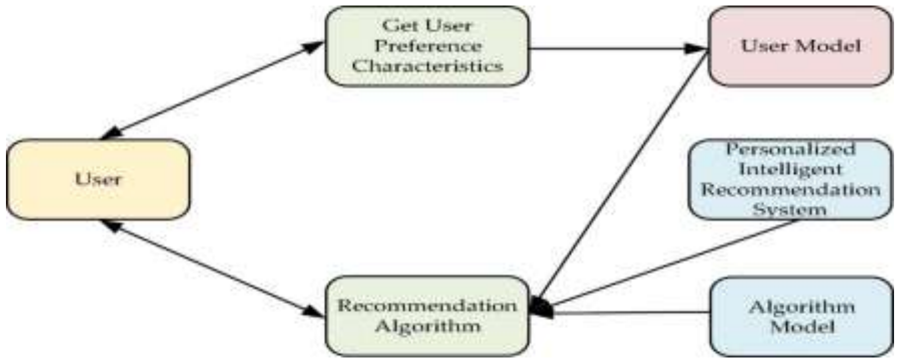

Fig. 1: Personalized Model [10].

Given the fast growth of digital learning materials and scientific research data, the study's backdrop highlights the increasing importance of intelligent recommendation systems in the field of education. While managing vast amounts of data, traditional teaching methods and learning environments sometimes find it difficult to meet the variety of student learning demands. This restriction results in inconsistent student performance, ineffective information delivery, and a lack of customization in learning paths. In order to overcome these obstacles, intelligent recommendation systems include cutting-edge computational methods that can evaluate intricate information and generate insightful conclusions. A more flexible and individualized learning environment is offered by these technologies, which bridge the gap between unprocessed educational data and practical learning techniques [10].

The key importance of ML in developing these systems is further highlighted in the paper. To turn raw data into useful information that can direct instructors and students, methods including data preparation, feature extraction, and predictive modelling are used. By revealing hidden trends in research activity and student performance data, these models help create suggestions that fit both specific learner profiles and more general academic goals. Crucially, the system can adjust to various data kinds and situations thanks to the utilization of both supervised and unsupervised machine learning techniques. Because of their versatility, intelligent recommendation systems may be used in a variety of educational and research contexts and are not limited to a specific application [10].

3. Literature Review

With a focus on both Using traditional ML methods and sophisticated deep learning models, research on forecasting student performance and developing intelligent study suggestion systems has intensified. Traditional algorithms such as KNN, SVM have been widely employed in educational datasets to estimate student outcomes [34], [36]. These methods have proven useful in classifying students into categories such as pass/fail or grade groups, although challenges remain when dealing with limited datasets [33]. To overcome these limitations, recent work has shifted toward deep learning models, which provide improved accuracy and generalization. Models such as [1], hybrid CNN-RNN architectures [37], and other deep learning variants [38] have shown significant promise in capturing complex learning patterns, while explainable models based on personalized attention mechanisms [39] provide deeper insights into reasons for student underperformance.

In parallel with predictive modelling, intelligent the purposed system is to provide personalized support to pupils. Early systems applied machine learning for course selection and performance-based recommendations [9], [12]. More recent approaches have integrated academic performance prediction with recommendation, allowing for mobile-based applications [3], automated academic advising systems [19], and reinforcement learning-based test scheduling [2]. At the same time, large-scale e-learning platforms have adopted AI-based assessment and recommendation systems capable of handling big data contexts [5]. Other research has explored multi-criteria optimization for course selection [18], knowledge state-based adaptive platforms [17], and hybrid classification approaches to improve recommendation accuracy [40]. Collectively, these systems demonstrate the growing sophistication of educational recommender systems, moving beyond simple filtering to hybrid and AI-driven strategies.

Research trends and gaps in this field have also been better understood because to systematic reviews and surveys. Numerous evaluations have emphasized the expanding use of hybrid & DL approaches in student performance achievment & educational recommendation systems. [23, 24], 25], 29], and 41. These reviews emphasize challenges such as data sparsity, explain ability, and the need for context-aware personalization, while also pointing toward future opportunities for scalable and ethical applications. Additional studies have shown that both cognitive and non-cognitive features can significantly improve predictive performance [7], [10], reinforcing the importance of holistic student modelling.

Finally, intelligent systems have also been applied to grading and assessment, linking prediction with automated evaluation. Examples include automated grading systems with adaptive feedback [16], grading management platforms in school settings [14], and AI-based student grading models [13]. These applications illustrate the real-world implementation potential of intelligent systems, extending beyond predictive research into practical educational environments. Overall, the literature demonstrates a clear evolution from conventional machine learning models toward hybrid, deep learning, and explainable AI approaches, while highlighting persistent challenges in data availability, system generalizability, and integration with educational practice.

Year & Reference	Approach / System	Techniques / Algorithms	Dataset Used	Key Contribution	Limitation
2022 – [5]	AISAR RS	AI + Big Data analytics	E-learning big data	AI-driven student assessment + RS	Requires large-scale infrastructure
2023 – [19]	Academic Advising RS	Curriculum Analysis + Performance Modelling	University curriculum data	Automated advising with performance-based insights	Limited scalability
2024 – [3]	Mobile Academic RS	Classification + AI	840 students (higher ed.)	Early prediction + mobile-based recommendations	Limited to specific dataset
2024 – [6]	Student Performance Prediction	Random Forest, Extra Trees, KNN	Baghdad Univ. dataset	High accuracy prediction of student success	Dataset limited to one institution
2024 – [18]	Elective Course RS	Hybrid + Genetic Optimization	University course data	Multi-criteria recommendation for course selection	Optimization complexity
2024 – [30]	Academic Planning RS	Multimodal ML + EDM	University data	Predicts grades + recommends course planning	Context-specific dataset
2025 – [38]	Hybrid DL Prediction	Hybrid Deep Learning Models	Undergraduate student data	Achieves high accuracy with hybrid DL	Lacks interpretability, black-box issue

Table 1: Comparison table of Research Paper

3.1 Available Datasets

Assessment logs: Logs were collected from computerized assessments, usually test scores, student attempts, and scheduling behavior. These logs were used to train reinforcement learning models to generate adaptive and personalized test schedules so as to improve academic performance [2].

Student academic records (mobile-based system): Academic information from 840 college students, including grades, participation in classes, and performance classifications (high, medium, and low). A mobile-based system that forecasts early academic standing and offers tailored recommendations was developed using this information [3].

E-learning Big Data (AISAR): vast amounts of data from online learning environments, including performance ratings, evaluations, course interactions, and login histories. This information enabled an AI-driven system for student assessment and suggestions that adapts to behavioral and performance trends [5].

Baghdad University dataset: Actual student information from Baghdad University, such as demographics, grades, test results, and attendance records. In order to predict student performance, ML algorithms including RF, KNN were trained using this dataset [6].

Scientific research & academic datasets: Information pertaining to academic and research endeavors, such as research results, publication histories, and the utilization of educational resources. In the context of sustainable education, this dataset was used to create intelligent recommendation systems [10].

University course selection dataset: Academic information that includes prior grades, elective enrollments, and student preferences. This dataset was used to help students choose elective courses by combining genetic optimization with hybrid multi-criteria recommendation systems [18].

4. Methodology of Review

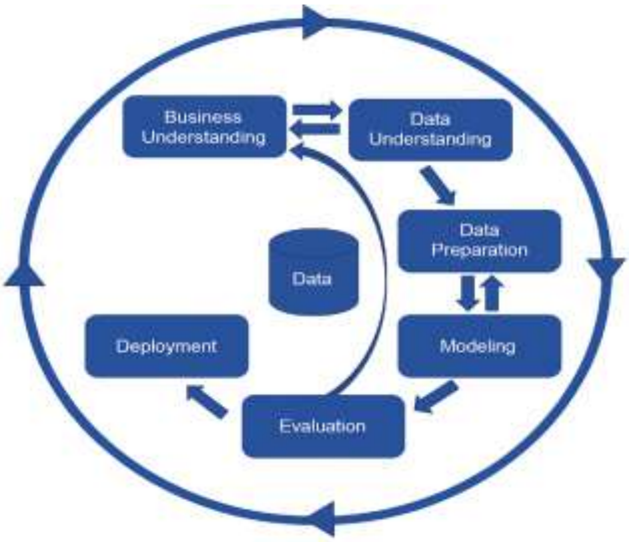

Fig. 2: Methodology of Data Mining [11].

A. Business Understanding

This study proposed a prediction model and recommendation system for student academic achievement based on educational data in an attempt to improve communication between teachers and students and possibly improve learning settings [11].

Qualities that were expected to directly affect students' rankings were part of the selection process. After that, the students were split up into three groups—enrolled, dropout, and graduate—and given different supervised learning techniques. The recommendation algorithm ultimately suggested learning tactics based on the pupils' current position [11].

B. Data Understanding

The dataset utilized in this study came from "Predict students' dropout and academic success." This dataset provides a thorough overview of the students involved in various university programs. This includes data in demographics, academic performance, and socioeconomic traits that can be used to investigate possible factors influencing academic success and student dropout. The target characteristics of these all students.

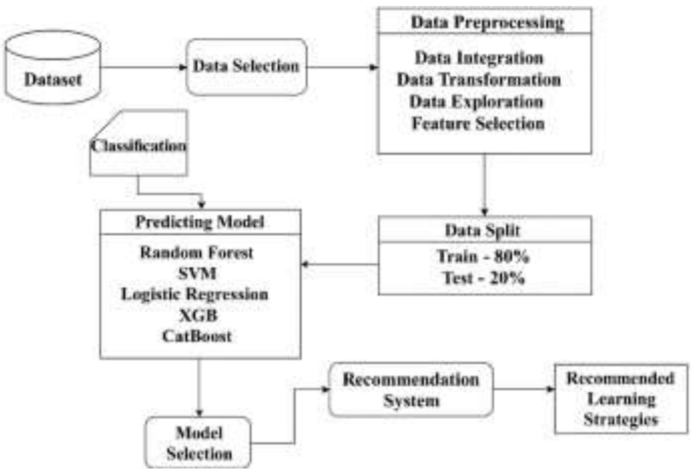

Fig. 3. Methods for prediction model [11].

C. Data Preparation

A critical phase in knowledge discovery is data pre-processing, which includes feature selection, reduction, transformation, and cleaning. It entails checking the dataset for undesirable values, removing fields that aren't important, and formatting the cleaned data appropriately for machine learning algorithms that work well [11]. This step involved like columns of categorical data & replacing numerical values with names, verifying missing and duplicate data, and more.

D. Modelling

DM, according to earlier research, is the process of developing models for classification, prediction, or uncovering hidden patterns in publicly available data [11]. These days, supervised and unsupervised data mining are the two most common forms of data mining. On the other hand, unsupervised algorithms enable the analysis of hidden patterns without the need of a target variable, whereas supervised algorithms function by learning the category of unseen data [19]. Supervised methods such as SVM, RF, XGB, LR, and CB classifiers were used to create the models for this investigation.

E. Evaluation

Several metrics are use in development of the models' performance, including recall, F1-score, accuracy, and precision. The measures listed below are used to assess models [11].

1) Precision
2) Recall
3) Accuracy
4) F1-Score

F. Deployment

The system offered beneficial learning tactics and anticipated outcomes of students like dropout, and enrolled in university area. Users can enter socioeconomic, academic, and demographic information into the system. Python served as the study's main computer language. Models were implemented using a machine learning tool like Scikit-Learn. Using Matplotlib and Seaborn, data distributions and performance metrics were shown [11].

5. Future scope

Although the reinforcement learning–based recommendation system developed in this study demonstrates strong potential for adaptive computerized assessments, several directions remain for future research. First, the current system was tested only on reading assessments for fourth-grade students. Future studies should extend the approach to other subject areas, such as mathematics and science, and across multiple grade levels to evaluate its generalizability. Second, the fairness and effectiveness of the system across diverse subgroups of students—such as by gender, grade, or language background—require further examination. For intelligent educational methods to be widely adopted, equity must be guaranteed. Additionally, while the study employed an actor–critic reinforcement learning framework, alternative approaches such as collaborative filtering or hybrid models could be investigated, especially for smaller datasets where reinforcement learning may not be practical. Moreover, future work should analyse the system's performance across achievement levels, comparing how well it supports both high- and low-performing students. Finally. There is still opportunity for investigation into the practical concerns of scalability and deployment in actual classroom environments. To further the use of such systems in regular educational practice, it will be essential to investigate teacher uptake, integration with current educational platforms, and sustained student involvement [2].

6. Conclusion

With an emphasis on forecasting student success and offering individualized learning help, this research has looked at the state of intelligent study recommendation systems. Current research shows that deep learning and machine learning methods like reinforcement learning, RF, and ANN may accurately forecast research results and inform adaptive suggestions. The ability to tailor resources to each learner's requirements has also been shown via recommender tactics. Most systems rely heavily on academic data from limited or institution-specific datasets, overlooking behavioral and socio-emotional factors that are equally critical to student success. Issues of fairness, scalability, and explainability also pose barriers to broader adoption. Overall, intelligent study recommendation systems hold strong potential to enhance student learning, reduce dropout risks, and support holistic educational development. Addressing current limitations through larger, more diverse datasets, integration of psychological and behavioural attributes, and deployment in real-world environments will be essential for realizing their full impact. The future of education lies in building transparent, adaptive, and scalable recommendation systems that can meaningfully transform the teaching and learning experience.

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