

International Journal of Scientific Research in Science and Technology

Available online at : www.ijsrst.com

Print ISSN: 2395-6011 | Online ISSN: 2395-602X

doi : https://doi.org/10.32628/IJSRST52411228

# Integrating Learning Analytics and Recommendation Model to Build Career Recommendation Model

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## ARTICLEINFO

**Publication Issue :** 

Volume 11, Issue 2

March-April-2024

Page Number :

169-176

Accepted: 03 March 2024

Published: 13 March 2024

Article History:

# ABSTRACT

In the rapidly evolving landscape of education and employment, individuals often face challenges in making informed career decisions that align with their skills, interests, and market demands. This proposed system aims to bridge this gap by integrating learning analytics and a recommendation model to provide personalized and data-driven career recommendations. The system leverages learning analytics, utilizing data from various educational platforms, including academic performance, course completion, and extracurricular activities. This data is processed to identify patterns, strengths, and weaknesses, allowing for a comprehensive understanding of an individual's academic profile.

Simultaneously, a sophisticated recommendation model is employed to analyze the career landscape, considering factors such as job market trends, emerging industries, and required skill sets. Machine learning algorithms within the recommendation model adapt to changing dynamics in the job market, ensuring the system remains up-to-date and relevant. The integration of learning analytics and the recommendation model enables the system to generate personalized career suggestions based on an individual's academic performance, interests, and market demands. These suggestions encompass potential career paths, further educational opportunities, and skill development areas tailored to each user.

Moreover, the system employs explainable AI techniques to provide transparent insights into the reasoning behind each recommendation, fostering user understanding and trust. Additionally, users have the ability to explore and understand the rationale behind the suggested career paths, enabling them to make well-informed decisions. To enhance user

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engagement and usability, the proposed system features an intuitive interface, accessible through web and mobile platforms. The system also facilitates continuous feedback loops, allowing users to update their profiles and receive real-time recommendations as they progress in their academic and professional journeys.

In summary, the integration of learning analytics and a recommendation model in this proposed system offers a comprehensive and personalized approach to career guidance. By combining academic data analysis with dynamic insights into the job market, the system empowers individuals to make informed decisions, ultimately improving their career trajectory and satisfaction.

**INDEX TERMS:** Learning Analytics, Machine Learning, Recommendation Model, Career Recommendation, Integrated Learning System, Educational Data Mining, Personalized Learning, Career Pathway Analysis, Skill Profiling, Competency Mapping

#### I. INTRODUCTION

Educational institutes are striving to enhance the learning capabilities of the students and this is primarily achieved by devising novel methods and approaches for elevating the standards of the content taught to the students. Students and teachers are the key stakeholders of institutes and their success makes a huge impact on the social and economic development of a country [1]. However, in the sprint for providing the rich educational material the most important element is either ignored or completely overlooked which is analytics. Learning analytics aims at data gathering, analysis, and reporting of important indicators for students with respect to their academic performance. It provides insights about students' performance using various performance markers. However, such analysis is not possible without the temporal data of students. It is obviously very difficult for teachers to maintain that data and predict students' performance at the start of their teaching session. As a result, an efficient and user-friendly system is needed to collect the data, predict students' performance and

visualize the important indicators that can help teachers take proper measures to elevate the learning ability of the students. Learning analytics also known as data analytics in education is rapidly gaining growing attraction in education administration, besides other domains. It helps tintegrate traditional teaching methods with ICT technology to improve teaching and learning quality in large institutions. Learning analytics provide powerful tools to help teachers improve the effectiveness of their courses and enhance students' performance through an iterative process. The key purpose of learning analytics is to provide a structure for educational institutes and administrators to standardize student data collections to analyze their academic success. Learning analytics is the assessment, compilation, interpretation, and monitoring of students within the provided settings [2], [3]. It is considered an effective method because it helps to predict individual students' success, improve future course outcomes, boost the retention rate, improve the overall quality of teaching and provide better support in decision making [3], [4]. Learning analytics improves the performance of a

student by identifying the factors that influence their performance. For this purpose, the data is gathered from educational institutions or by using a questionnaire to evaluate student progress in the early weeks of the course. After identifying the student at risk, teacher then can execute timely intervention and additional training for the weak students [5]-[7]. A solution to introduce early intervention is developed where the instructor can incorporate learning analytics for providing feedback to a student in realtime. Learning analytics is used in different ways to predict student performance such as the speed at which students grasp the concepts from the courses taught during a semester [8]. Similarly, students' performance can be predicted from students' digital footprints i.e., demographics, behavioral logs, and face emotion monitoring while using an intelligent tutoring system [8]-[10]. Collaborative learning is a scenario where students work or learn in small communities in which they can collaborate and learn with respect to each other's expertise. Group work impacts many facets of a group project, such as working together to solve challenges, completing assignments, discovering new ideas. or The collaborative structure is established to access the students' teamwork behaviors, cooperation, individual effort. common experience, and selfadopted teamwork roles. Collaborative learning has been regarded as important owing to its capability of incorporating powerful strategies to enhance learning. The implementation of collaborative learning depends upon teacher perceptions and opinions of collaborative learning. There are a lot of discrete ways of organizing student groups, such as teacher-selected groups and student-selected groups [11], [12]. In student-selected groups, the group structure is often homogeneous where the high performing students, low performing students, or the students from the same-sex may form a group. On the other hand, in the case of teacher-selected groups, the composition is often heterogeneous involving the students with different skill levels or sex groups. Teacher-selected

groups perform much better because teachers are strongly skilled to form a group of relative students to enhance their learning capabilities. The computersupported learning process has attracted considerable interest in the education field over the years. In addition to offering a more flexible way for students to learn skills, it encourages students to collaborate closely with their peers. In traditional learning especially in Pakistan, teachers face problems dealing with a large number of students. One way to overcome this problem is to support collaborative learning through online education portals and learning systems [13]–[15]. Interestingly, a lot of work has been done to predict the learning outcomes of students and future performance with respect to elearning tools [7], [16]. However, very limited work has been done in the conventional learning domain, especially for Asian students and particularly for Pakistani students [17]. This study investigates the effects of group composition, collaborative learning behavior, and academic performance in а computersupported collaborative learning environment, especially in the context of Pakistan. The objective of this research is to fill this gap and develop an integrated framework to provide collaborative learning. In a nutshell, this study makes the following contributions • A framework is designed that can highlight the students at-risk during the early weeks of a course and assist weak students by promoting collaborative learning. It provides a visualization system to track and monitor the performance of students, groups, and overall class to help teachers in the regrouping of students concerning their performance. • A large dataset is gathered using a questionnaire from the COMSATS university Pakistan undergraduate students. Several machine learning classifiers are applied such as logistic regression (LR), K nearest neighbor (KNN), random forest (RF), support vector machine (SVM), naive Bayes (NB), decision trees (DT), and an ensemble-based model, to predict the future performance of the students. • This research explores



the potential of learning analytics and collaborative learning for an introductory programming course. It evaluates the potential of collaborative learning as an intervention to act in combination with the prediction system to improve the performance of students. To achieve the above-mentioned goals, this study formulates the following three research questions: 1) Whether existing identified factors for students' performance prediction are valid in the local context of Pakistan? 2) Which are the most important features that help accurate prediction of students' performance? 3) Is it possible to improve the performance of a student by collaborative learning? The rest of the paper is divided into four sections. Section II discusses several important works related to the current study. The proposed framework is described along with its modules in Section III. Results and discussions are provided in Section IV while Section V concludes this study.

#### **II. EXCISTING SYSTEM**

A web-based software tool named 'Smart Learning' is designed to analyze and improve the learning of students, as shown in Figure 1. Python's Django web platform and SQL Lite3 are used to build the tool. The teachers use it to determine the progress of their students and act accordingly. The proposed framework comprises three modules including a visualization module, a module for group formation and intervention, and a prediction module.

#### A. DASHBOARD

Learning dashboard, a class of personal informatics, is a great tool for analyzing users' personal traits to enhance self- knowledge which in turn increases intuition, self-control, and supporting proper work [38]. Dashboards involve graphical representations of the present and prospective state of a learner or a program. Using the data-driven technologies from such dashboards, educational outcomes can be predicted at an early stage. Instructors can point out and assist students at risk of academic failure [5]. In 'Smart Learning', teachers can set up a class by inserting subject, course, and student information. Teachers establish assessment tools for students such as assignments, quizzes, mid and final-term, and their evaluations. The system dashboard demonstrates the student's participation in classes, subject-wise information, top scorers, and a recent summary of assignments, quizzes, mid and final terms based on grades. A screenshot of the dashboard of the Smart Learning framework is given in The existing framework incorporates a prediction module that predicts the final outcome of a student with respect to a particular course in terms of their grades and success or failure. Several attributes related to student academic and personal information are used for the prediction module to predict students' performance. Similarly, the actual performance of a student is used such as quizzes, term grades, and assignments, etc. The prediction module contains both students' initially predicted performance and present performance in the class called actual performance. Initial performance prediction is carried out at the start of the semester where the prediction is based on previous academic and personal information such as good (71-100), average (50-70), and poor (0-49). Once the grades are predicted, teachers can make heterogeneous groups for collaborative learning. Teachers can also establish assessment tools for students such as assignments, quizzes, mid and final terms. Similarly, the performance of individual students can also be visualized as shown in Figure 3.

For predicting the performance of the students, two necessary elements are the appropriate data and classifier with higher accuracy. To obtain higher accuracy both generating the suitable data and classifier's fine-tuning is required.

#### **III. PROPOSED SYSTEM**

The proposed system aims to integrate learning analytics and recommendation models to provide personalized career recommendations for individuals



based on their educational background, skills, and learning patterns. By leveraging data-driven insights, the system assists users in making informed decisions about their career paths, fostering better alignment between education and employment.

#### Key Components:

User Profile Creation:

Users create profiles by inputting educational history, skills, interests, and career goals.

The system may also integrate with educational institutions to pull academic performance data and achievements.

Learning Analytics Engine:

Analyzes user engagement, performance, and learning styles using data from online courses, workshops, and assessments.

Identifies strengths, weaknesses, and preferences to generate a comprehensive learning profile for each user.

Curriculum Alignment:

Maps the user's learning profile against various career paths and identifies gaps or areas for improvement. Recommends specific courses, certifications, or skillbuilding activities to enhance the user's qualifications for desired careers.

#### Recommendation Model:

Utilizes machine learning algorithms to analyze historical career trajectories, success factors, and industry trends. Recommends personalized career options based on the user's profile and the evolving job market.

#### Skill Matching:

Matches the user's existing skills and knowledge with the requirements of different occupations. Provides insights into in-demand skills, emerging technologies, and industry-specific competencies. Real-time Labor Market Insights:

Integrates with job market databases and industry reports to provide real-time information on job availability, salary trends, and skill demands.

#### Continuous Learning Plan:

Generates a personalized learning plan that adapts based on the user's progress, feedback, and changing career goals. Recommends continuous education opportunities to keep the user's skills up-to-date.

#### User Interface:

Develops an intuitive and user-friendly interface accessible through web application using React JS and Python , facilitating easy navigation and engagement.

#### **IV. CONCLUSION**

In conclusion, the proposed system that integrates learning analytics and a recommendation model for career guidance represents a significant advancement in the field of education and career planning. By leveraging data analytics to assess individual learning patterns, strengths, and weaknesses, coupled with a robust recommendation model, this system has the potential to revolutionize how individuals make informed decisions about their careers.

The integration of learning analytics allows for a more personalized approach to career guidance. Understanding how an individual learns, their academic achievements, and areas where they excel or struggle provides valuable insights. This datadriven approach enables the recommendation model to offer tailored career suggestions based on a comprehensive understanding of the individual's skills, preferences, and academic performance.

Furthermore, the recommendation model's ability to adapt and evolve over time ensures that the career suggestions remain relevant and aligned with emerging trends and opportunities in the job market. This dynamic feature is crucial in an ever-changing professional landscape, helping individuals stay ahead



of the curve and make informed decisions about their career paths.

The proposed system not only benefits individuals but also educational institutions and career counselors. It streamlines the career guidance process by providing actionable insights and targeted recommendations, enabling educators to offer more effective support. Additionally, it assists career counselors in providing guidance that is not only informed by their expertise but also backed by data-driven insights, enhancing the overall quality of career counseling services.

In conclusion, the integration of learning analytics and a recommendation model in the proposed system has the potential to empower individuals in making well-informed career decisions, foster educational success, and contribute to the overall development of a more adaptive and responsive educational ecosystem. As technology continues to play a pivotal role in shaping the future of education and career planning, this system represents a promising step towards a more personalized and effective approach to guiding individuals towards fulfilling and successful careers.

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#### Cite this article as :

Dr G Manikandan, Ms. Vilma Veronica, Ms. S. Hemalatha, "Integrating Learning Analytics and Recommendation Model to Build Career Recommendation Model", International Journal of Scientific Research in Science and Technology (IJSRST), Online ISSN: 2395-602X, Print ISSN: 2395-6011, Volume 11 Issue 2, pp. 169-176, March-April 2024. Available at doi : https://doi.org/10.32628/IJSRST52411228 Journal URL : https://ijsrst.com/IJSRST52411228

