

### AI-Powered Student Dropout Prediction & Personalized Learning System

Ms. S. Jayashree, Assistant Professor , Manoj D (711722104065),\* Sharan R (711722104099),

\* Siddharth N R (711722104102),\* Vishal S (711722104314)\*

Department of Computer Science and Engineering,  
KGISL Institute of Technology, Coimbatore, India

**Abstract**—As the technologies entered the new phase using artificial intelligence in many sectors and results in improvised performance by reducing time spent over simple analysis which is done manually, in this phase of evolution the modern education systems use many online tools for teaching and learning. Due to this, a large amount of students data is generated every day using these online learning platforms, assignments, tests and attendance records. Even-though this data is available, it is not utilized in proper way to support student at the right time. Due to this students results drops or they start thinking about leaving their course. In most of the institutions, student evaluations are still depends mostly on final exams and grades. This makes it difficult for institutions to notice early signs of students academic difficulty. For students who lose interest slowly or miss classes are identified only after their performance becomes poor. At that stage, it becomes harder for them to be recovered. To overcome this issue, the student risk prediction and specialized learning support system is proposed. The system regularly collects student attendance records, academic scores, learning activity, and financial data. By using this data , it calculates a simple risk score that groups students into low, medium, or high risk levels. Separate dashboard are available for students, teachers and parents to view their progress and receive frequent updates. This approach of tracking students helps in taking early action, improving student participation, and reducing the chances of dropout.

**Key words:** Online learning platform, Specialized learning, Risk Level calculation, Online tools.

#### I. INTRODUCTION

With the rapid growth of online learning, students now spend more time in digital platforms for learning things than ever before. A lot of useful information like attendance details, test scores, login activities, and time spent on study platforms and overall participation were collected with the help of platforms that are used for attending classes, submitting assignments, taking quizzes, and accessing study materials. This data can be utilized properly which can help teachers to understand the learning pattern of student and identify where they are struggling. In many colleges and universities, this data is not used for the students support but used for gathering statistics and most of the decisions were made using the final exam results and end-semester grades. This traditional way of approach gives data about performance of the students only after they completing their exams. Academic problems like dropping of student performance usually do not happen suddenly. They decline slowly due to all factors like maintenance of poor attendance, low engagement in study platforms and classes, lack of understanding, or personal issues faced by their surroundings. Without monitoring regularly, teachers may find it difficult to know when a student is going to fall from their regular performance. These early identification of such patterns is important so that support can be provided for them before the situation becomes worse. To address this challenge, intelligent data analysis model which collects the behavioural patterns related to LMS (Learning Management System), the student data like assignment submission, attendance, login consistency, CGPA, financial information are used to conduct metrics that results in a overall risk percentage of student. In many cases students begin to face difficulties, they may start bunking classes, late submission of assignments, or spending less time on learning platforms which is noticed only after when the student's marks fall all of the sudden. By that time, the student may already feel demotivated, or disconnected from studies also feel stressed, which increases the risk of failure or dropout.

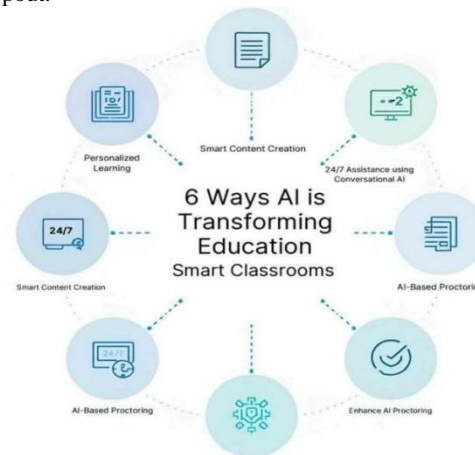


Fig. 1: Key Ways Artificial Intelligence is Transforming Modern Education

There are many ways where artificial intelligence is transforming education by making advancements to the existing education systems, it enhances the way how learning, teaching, and assessments are delivered. The place where AI provides its impact is in personalized learning, this is the phase where system analyze individual student performance, the pace of learning how quick are they are in learning a new concept, also the behavioral patterns to switch its pattern to adapt a individual students educational pattern and makes sure that every learner receives personalized teaching pattern sited to their strengths and areas where they need to be focused, rather than following a common instructional approach. AI also supports in more ways like the generation of educational resources such as practice exercises, summaries about large topics and adaptive learning materials that differs for every student. This will be reducing the workload for educators with assurance that students will be receiving academic content which is updated and relevant to their performance. The learning support for students is continuously strengthened through intelligent conversational assistance that allows learners to receive support and clarification at any time, making education more accessible.

There are assessment processes that have also become more reliable and efficient using AI-driven monitoring systems that help focusing on identification of student's academic risks at an early stage and support them through personalized learning ideas. A simple and accurate risk score is calculated using multiple indication factors like the assignment submission, attendance, login consistency, CGPA, financial information are used, ensures that the outcome is not determined with only single factor. Students will be receiving feedback about their learning status also their teachers have access to performance and risk insights of their students, and parents are informed through regular academic updates of their children. This approach brings responsibility, transparency, and collaboration among the stakeholders. The learning process becomes more student-centered and supports them when AI provides early intervention, continuous monitoring of their regular learning activities and also providing clear communication. This approach helps students to improve their engagement on study platforms, reducing the dropout risk, and overall academic experience is strengthened that helps them get adapted in this modern educational environment.

## II. LITERATURE SURVEY

Several studies have explored the use of intelligent data analysis and predictive techniques to understand student learning behavior and identify academic risks at an early stage. Most of these studies have focused on areas such as learning analytics, student dropout prediction, academic performance analysis, and personalized learning support. Different approaches use a wide range of data sources, including attendance records, assessment results, online activity logs, and engagement metrics. Although these methods show promising results, their effectiveness varies based on data quality, system design, and practical development challenges. In 2015, Lakkaraju et al. proposed a machine learning framework to identify students at risk of adverse academic outcomes by analyzing behavioral data collected from online learning platforms. The study demonstrated that early warning signs could be detected well before the final assessments, allowing educators to take timely action. However, the framework depends on complex models that lack transparency, making it difficult for teachers to understand how predictions are generated. This limitation reduces trust in the system and affects its practical adoption in real educational environments. Williamson et al. (2020) examined the role of the artificial intelligence in supporting personalized learning within modern education systems. The study discussed how data-driven systems can adapt learning content based on individual student needs and their learning styles. It also highlighted important concerns related to data privacy, ethical use, and policy-level discussions; however, it did not offer a technical framework or implementation strategy for real-time student monitoring or risk prediction.

Alyahyan and Dustegor (2020) presented a detailed literature review on predicting academic success in higher education. They work analyzed various prediction models and identified key factors, such as attendance, assessment scores, and student engagement, as strong indicators of academic performance. This study provides useful best practices and guidelines for future research. However, the focus remained largely theoretical, with limited discussions on system architecture, real-time processing, or practical development in academic institutions. In another study, Williamson et al. (2020) explored the impact of AI-driven personalization in educational systems, with a strong focus on fairness, bias, and governance issues. The authors emphasized the importance of responsible data usage and transparency in decision-making. Although this study offered valuable insights into ethical considerations, it did not evaluate prediction accuracy or provide experimental results related to student risk assessment.

Aljohani et al. (2022) proposed an AI-based dropout prediction system that used behavioral patterns such as login frequency, assignment submission history, and participation levels. Their model achieved good accuracy in identifying students who were likely to drop out of school. However, the system mainly focused on prediction and did not provide personalized learning guidance or clear recommendation for students after risk identification. The absence of direct intervention strategies limits its overall impact on student support.

Jayaprakash et al. (2018) introduced an early alert system that used data from learning managements systems to identify academically at risk students. The system generated alerts for instructors when students showed signs of disengagement or poor performance. While the approach helped instructors respond faster, it did not include a feedback mechanism for students or communication support for parents, which reduced its effectiveness as a complete academic support system.

Rai and Jain (2021) developed a student performance prediction system using machine learning techniques applied to attendance and internal assessment data. The system performed well on smaller datasets and provided reasonable predictions. However, when applied to larger and more diverse student populations, the accuracy decreased, indicating scalability limitations and the need for more robust feature-handling.

Fernandez et al. (2020) designed a learning analytics dashboard that allows educators to visualize student progress, engagement levels, and performance trends. The dashboard improved monitoring and decision-making by presenting the data in an easy-to-understand format. However, the system does not include automated risk scoring or predictive analytics, requiring educators to manually interpret trends and identify at-risk students.

In 2021, Hassan et al. proposed a deep learning-based framework for predicting student's academic risk. The model demonstrated strong prediction performance by capturing complex behavioral patterns in the student data. Despite its accuracy, this approach requires high computational resources and complex infrastructure, making it less suitable for institutions with limited technical and financial resources.

### A. Summary of Literature Review

From the review of existing research, it is clear that AI-based systems have helped improve the prediction of academic risk and the analysis of student learning behavior. Many studies have successfully used attendance data, assessment scores, and online activities to achieve higher prediction accuracy, but they do not fully address how the results can be clearly explained and used for real academic support.

The major limitations identified include the following:

- One major issue is the lack of simple and easily explainable risk-scoring methods. In many systems, the prediction process is complex, and teachers or students are unable to understand how a particular risk level is assigned. This reduces trust in the system and makes it difficult for educators to act confidently based on the predictions.
- Another limitation is the limited availability of personalized learning recommendations. While many systems can identify at-risk students, they often stop at prediction and do not guide students on how to updated. Without clear study plans or subject-wise suggestions, students may not know what actions to take after being identified as at risk.
- Minimal parental involvement is also a common drawback. Most existing systems are designed mainly for students and teachers, with very little focus on keeping parents informed. Consequently, parents receive delayed or incomplete information about their children's academic progress, reducing their ability to provide timely support.
- Additionally, several systems rely on high computational resources or complex architectures, such as deep learning models or heavy cloud infrastructures. This setup increases the implementation cost and makes it difficult to deploy institutions with limited technical resources.

The proposed system overcomes this limitation by using a Python-based AI framework that combines academic performance, attendance, and behavioral activity data. It generates clear and easy-to-understand risk sources that can be interrupted by both technical and non-technical users. The system also provides personalized study suggestions to guide students toward improvement and ensures transparent communication among students, teachers, and parents through a single, integrated platform.

### III. PROBLEM STATEMENT

From the study made on the existing research, it makes clear that most of the existing student monitoring systems try to predict only the student performance that is utilized only for statistic purposes, but very few can identify the problems faced by students during the learning at an early stage and provide them proper support on time. In most of the cases, students are noticed only after they lose their interest or after the degradation of academic performance. Because of the delay in identifying problems early, it becomes harder to help students to recover. However, several gaps are remain in the current systems.

The major gaps identified include the following:

Limited use of continuous learning and behavioral data

Most of the existing systems use only the marks scored in examinations and attendance percentage of the student. They actually do not completely consider their learning behaviours, such as login activities, the student participation in extracurricular activities, or assignment submission patterns. Therefore, early signs of learning difficulties are often ignored.

Lack of clear and simple risk scoring

Most of the systems provide results that are difficult to understand by a new user. Students and teachers cannot clearly understand why a student is marked as at-risk, without a simple risk score value, it becomes harder to take the right action at the right time with lack of clear and simple risk scoring.

No clear learning guidance after risk was found

Some systems are only capable of identifying the struggling students, but they are not capable of guiding them on their next steps to overcome their struggle. There are not any clear personalized study suggestions or personalized steps for their improvement, Which is the main factor that leads students to lack proper guidance.

Very little role for parents in monitoring

In many systems parents are not included often in monitoring of academic process of their children, and parents receive only limited or delayed information about their child's progress that reduces their ability to support students early, where as here they can monitor performance in real-time, Problem Statement: The student monitoring systems currently used are incapable of identifying academic risk at an early stage and do not provide support on right time. Lot of systems use late examination results at the end of the semester and do not consider regular learning behavior observed by the achievements and quiz taken by students online. Also there is a communication gap between the students, parents and teachers. Due to that, there is a need for a simple student risk prediction system that is capable of using academic and learning data without any stopping factors, also provides an risk score that is easy-to-understand, gives personalized study guidance, and supports communication gap between students, teacher, and parents to improve academic progress of the students.

### IV. PROPOSED SYSTEM (NOVELTY)

The proposed system presents an AI-driven academic monitoring framework that is designed to identify at-risk students and provide support for them at the right time. It is a system that integrates multiple data indicators, such as attendance percentage, semester assessment scores, quiz performance and learning activity records. These indicators work together to capture different academic risk conditions accurately and provides a risk score, some of academic risk conditions, including:

Decline in academic performance despite regular attendance

There are several cases in which students attend classes regularly but still results in a regular drop in marks and assessment scores. This might be due to the lack of understanding wide topics, learning gaps, or difficulty in specific subjects. This condition can be identified by the system when comparing attendance records with the academic performance trends to provide the students a personalized learning schedule.

Consistent absenteeism leads to reduced engagement

In certain cases there will be regular absence of students from classes that often results in missing out lessons and reduced participation in academics. When time passes this affects the interest they have in learning and their performance will be reduced academically. The system tracks attendance pattern of the students and identifies the students who are all frequently absent which leads to low engagement and decline in academic performance.

Low quiz scores indicate weak subject understanding

The student's understanding level of topics taught in classes can be tested and measured using the quizzes. When the student have repeated low scores in daily quizzes, that indicates the student is struggling to grasp concepts. The system monitors every quiz performance of the student and highlights subjects in which they need additional support.

Sudden drop in learning activity suggesting disengagement

The sudden drop in learning activity can be identified by decrease in login frequency, study time taken by students, or assignment submission may indicate the loss of interest or external challenges like financial struggle and mental health instability. The system will be continuously monitoring learning activity logs to mention such changes and tag students who are not interested and showing signs of disengagement from the learning process.

The back-end of the system acts as the central processing unit that collects, processes and analyzes the student data using machine learning models and rules-based segregating logic. The data that have been processed are then updated continuously and visualized in real-time through interactive dashboards and statistical charts that every new users can understand, these dashboards are available to the teachers, students and the administrators. There is a threshold value defined for the risk levels classified into low, medium and high, when the student risk level crosses this threshold the system automatically send alert to the respective faculty and parent through the platform. This helps academic coordinators to enable early intervention, scheduling timely counselling for students at-risk and providing support both financially and academically before they reach a critical stage. Multi factor data verification is combined with continuous analytics made by machine learning models and role-based monitoring, the proposed system will be ensuring higher prediction accuracy, transparency, and practical usability for real-time which makes it a reliable solution that improves student success rate and reduces dropout rate of the student.

### V. FLOW DIAGRAM FOR : AI-POWERED STUDENT DROPOUT PREDICTION & PERSONALIZED LEARNING SYSTEM

The weekly student activity timeline shows the student's weekly activity explains how student interact with the academic system over the course of a week. The different learning and academic actions performed by a student from Monday to Friday is visually represented. The activities are placed along a straight line to show how the order works and student's behavioral cycle.

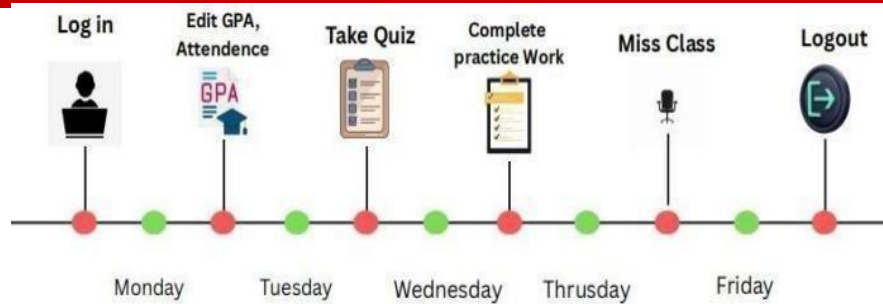


Fig. 2: Mini Flow Diagram from Literature Review: AI- POWERED STUDENT DROPUT PREDICTION&PERSONALIZED LEARNING SYSTEM

At the beginning the student will be logging into the student portal to get access from the learning system. When the student continuously login it is marked as active participation, where as irregular logins like few days in a week will be marked as the student is not engaged with the platform often. This reflects on the student’s academic performance calculation and attendance records, which are important indicating factors of learning consistency and performance. There is a stage that represents the assignment submissions or practice exercises taken by the students regularly to maintain their consistent practice for improving their academics. This activity shows how regularly students practice using learning materials like quizzes. Consistent practice of a student indicates his good engagement in study platform, whereas missing the quizzes and tasks assigned may indicate that there is a learning gap for the particular student.

There is a stage that represents the classes missed by the student, it highlights the days when the students does not attend their scheduled classes. When the student start missing classes frequently that may lead to poor understanding of concepts they missed and it will be a decline for their learning progress, student with repeated low quiz activity or missed quizzes can lead to academic difficulty.

Finally, the Logout activity shows the end of the interaction between student and the academic system. When combined with login data, it helps system to measure the total time student spends on learning activity.

VI. SYSTEM ARCHITECTURE

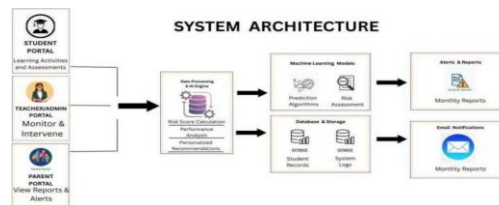


Fig.3: System Architecture: AI- POWERED STUDENT DROPUT PREDICTION&PERSONALIZED LEARNING SYSTEM

The design uses modular architecture in which the majority of the function of the application is handled by a separate layer that improves clarity, flexibility, and makes it easy for maintenance, also allowing each components to work on their own independently.

**Front-end Layer :**The user-facing components of the system is represented as the front-end layer. There are separate role-based interfaces that are provided for students, teachers, and parents. With the help of this layer , students can log in using their credentials, view their own academic performance, their attendance status, also their risk level that may bring awareness for them and take quizzes from personalized study suggestions.

The teachers can log in using their provided login-credentials to monitor student’s progress, analyze the overall performance of their class and review risk alerts to schedule counselling meeting for the student.

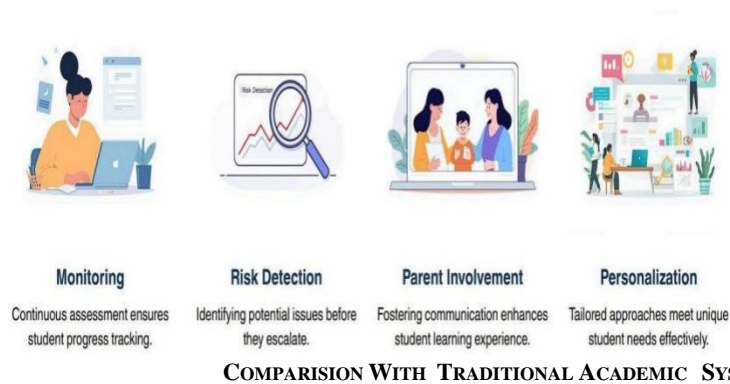
There are separate portal for parents to view their children’s progress, this portal provides periodic reports summarizing their children’s engagement to the academic platform and their educational status. The front-end was designed to be responsive, simple and easy to navigate so that the users with different technical gadgets could interact with the platform comfortably.

**Back-end Layer:**The core control unit of the system is the back-end layer. It manages the user authentication, role based verification to ensure there is no cross credential access between student and teacher portals and also provides secure access to system resources like student data and analytical information. This layer is responsible for the handling of business logic, such as processing attendance data, storing assessment results of students, management of user profiles of both student and teacher, and handling communication between modules. It also generates secure APIs that allows the front-end to be sending and receiving data efficiently. To ensure the data consistency, security, and smooth system operations the login is separated from the user interface.

**AI & Analytics Layer:** The meaningful insights that are generated by analyzing the student data is done by the AI and analytics layer. This layer processes multiple indicators like attendance records, academic scores, learning activities, and behavioral pattern of the student is used to calculate their risk score. Based on this score students were classified into three different risk levels(Low, Medium, High). The analytics is made to be transparent and understandable, that allows teachers and administrators to understand the results easily . The students who may require academic or financial support are identified earlier with the help of this analytical layer.

**Database Layer :**The database layer is responsible for the security and structured storage for every system datas. It consists of user profiles, academic records likes semester grades, and reports generated by the system. The users can only view information relevant to their role due to the strict database access control. This layer is responsible for the data integrity, privacy, and reliability, also enabling tracking of student performance.

The proposed AI-based student monitoring system collects academic and behavioral data such as attendance records, assessment scores, learning activities, and engagement levels, from the academic platform. These data were processed and analyzed using the machine learning models and sent securely to the back-end server where the risk pattern is identified. Based on multiple factors the students are classified into low-, medium-, or high-risk categories with the risk score calculated for the specific student data that have been collected. Once the risk level is identified, the system generates personalized study recommendations and start understanding study pattern of the students. A centralized dashboard is used by the teacher and administrators to view the risk summaries and performance rate of their students and academic updates of the students will be updated through email notifications for the respective parent of the students. The server side is responsible for handling of all processing and decision-making, ensuring data security, consistency, and reliability. This architecture supports early intervention, improves academic monitoring, and enables effective communication between students, teachers, and parents



VII.

**COMPARISON WITH TRADITIONAL ACADEMIC SYSTEMS**

Fig.4: Comparison with traditional academic systems : AI- POWERED STUDENT DROPUT PREDICTION&PERSONALIZED LEARNING SYSTEM

VIII. TOOLS AND DATABASE

The proposed system was implemented using a set of widely used tools that support web application development, data processing, and machine learning analysis. These tools were chosen to ensure smooth system performance, simple for development, and long-term scalability..

**Python** was used as the main programming language for the system. The back-end operations, data processing, and the implementation of machine learning model are handled using this. Python was selected because of its simplicity, reliability, and strong support for data analysis and artificial intelligence applications.

The **Flask framework** was used to build the server-side logic of the application. The user requests, page routing, role- based access control, and communication between the front end and the back end are managed by the flask. It also supports the structured integration of machine learning models and database operations.

**HTML, CSS, and JavaScript** were used to create simple and user- friendly web interfaces. These technologies allow students, teachers, and parents to interact with the system through dashboards, forms, and reports. The interface was designed to be easy to understand, responsive, and accessible across different devices.

A **PostgreSQL database** was used for secure and structured data storage. It stores student profiles, attendance records, academic scores, quiz results, learning activity logs, and calculated risk scores. PostgreSQL ensures data consistency, supports complex queries, and handles large volumes of academic data efficiently.

**Machine learning libraries** such as scikit-learn and XGBoost were, used to train the models and predict student risk levels. These libraries process historical and real-time data to identify patterns related to academic performance and engagement. The models help categorize students into different risk levels in a clear and understandable manner.

**Email services using SMTP** were integrated to send automated monthly reports and alerts to the parents, These emails provided summaries of student performance, attendance status, and risk levels, helping parents stay informed and involved in their children’s academic progress.

A Web-based dashboard was provided for students, teachers, and parents. Students can view their performance and learning suggestions, teachers can monitor progress and risk indicators, and parents can review reports and updates. This centralized dashboard ensures transparency and improves communication among all stakeholder



Fig.5:Risk Score Calculation & Category Mapping: AI- POWERED STUDENT DROPUT PREDICTION&PERSONALIZED LEARNING SYSTEM

The study presents a student risk prediction and personalized learning system designed to identify academic difficulties at an early stage and provide support at right time. Using attendance, academic performance, learning activity, and behavior data, the system generates a clear risk score that helps students, teachers, and parents take action in advance.

Unlike traditional methods that depends mainly on final exam results, the proposed system works continuously and highlights issues before they become serious problems. This allows for early support and reduces the risk of poor performance or dropout. Separate portals for students, teachers, and parents ensure transparency and shared responsibility in monitoring progress.

The system follows a student-friendly approach by maintaining data security, using clear explanations, and focusing on guidance rather than being a simple predictive platform. It supports teachers by reducing manual effort, helps students with personalized study suggestions, and keeps parents informed through regular reports.

Overall, the proposed system shows how intelligent data analysis can be used responsibly to improve learning outcomes and strengthen academic support in educational institutions.

## X. EXPECTED OUTCOME

The proposed AI-based Student Risk Prediction and Personalized Learning System is expected to bring meaningful improvements to academic monitoring and student support within educational institutions. By continuously analyzing student-related data, the system helps institutions move from reactive decision-making to early and informed intervention.

One of the key outcomes of this system is in the **early identification of students who are at academic risk**. Instead of waiting for semester-end results, the system detects warning signs, such as low attendance, declining quiz performance, reduced learning activity, and irregular engagement patterns. This allows institutions to recognize struggling students at an early stage when corrective actions are still effective.

The system also provides timely alerts and clear insights for teachers and parents. Teachers receive real-time updates through dashboards that highlight students requiring attention, along with the reasons for their risk status. Parents receive structured monthly reports that explain their children's academic conditions in a simple manner. This timely flow of information ensures that all responsible stakeholders are aware of the situation and can take action without delay.

Another important outcome is the delivery of personalized study guidance for students. Based on quiz results, subject-wise performance, and learning behavior, the system recommends specific topics and areas that require improvement. Instead of general advice, students receive focused guidance that helps them spend their time efficiently and improve their learning outcomes.

The system is also expected to improve student engagement and their overall academic performance. Features such as regular quizzes, progress tracking, and performance visualization encourage students to remain involved in their learning activities. As students become more aware of their strengths and weaknesses, they are more likely to develop consistent study habits.

By enabling early monitoring and structured intervention, the system helps reduce the risk of student dropouts. Students who might otherwise disengage or lose interest are identified early and supported through academic guidance, teacher involvement and parental awareness. This reduces the chances of students leaving their studies without completing them.

Finally, the system strengthens communication between students, teachers, and parents. All stakeholders operate within a shared information environment where performance data risk indicators and progress updates are clearly visible. This improved coordination promotes shared responsibility and creates a supportive academic ecosystem focuses on student success.

## XI. REFERENCES

- [1] A. Williamson Ben, D. Eynon, and R. Potter, "Personalized learning through artificial intelligence: Opportunities, risks, and policy perspectives," *British Journal of Educational Technology*, vol. 51, no. 6, pp. 1-17, 2020.
- [2] M. K. Aljohani, M. Fayoumi, and S. Hassan, "AI-based prediction of student dropout risk using behavioral patterns," *International Journal of Educational Technology in Higher Education*, vol. 19, no. 1, pp. 1-22, 2022.
- [3] A. S. Alyahyan and D. Dustegor, "Predicting academic success in higher education: A literature review and best practices," *International Journal of Educational Technology in Higher Education*, vol. 19, no. 1, pp. 1- 22, 2022.
- [4] S. S. Lakkaraju, E. Aguiar, and C. Shan, "A machine learning framework to identify students at risk of adverse academic outcomes," in *Proc. ACM Int. Conf. On Learning Analytics & Knowledge (LAK)*, pp. 1-10, 2015.
- [5] S. Jayaprakash, E. W. Moody, E. J. Lauria, J. R. Regan, and J. D. Baron, "Early alert of academically at-risk students: An open source analytics initiative," *Journal of Learning Analytics*, vol. 1, no. 1, pp. 6-47, 2014.
- [6] A. Kumar and R. Singh, "Student performance prediction using machine learning algorithms," *International Journal of Computer Applications*, vol. 175, no. 5, pp. 10-14, 2019.
- [7] M. Rai and A. Jain, "Predicting student academic performance using machine learning," *International Journal of Advanced Research in Computer*

- [8] R. Hassan, M. Ahmad, and S. Ali, "Deep learning based student risk prediction system," IEEE Access, vol. 9, pp. 102345-102356, 2021.
- [9] J. Fernandez, K. Baker, and J. Hawn, "Learning analytics dashboard applications in higher education," IEEE Transactions on Learning Technologies, vol. 13, no. 2, pp. 234-246, 2020.
- [10] S. Patil and R. Kulkarni, "AI-based academic performance monitoring system using cloud analytics," in Proc. Int. Conf. On Intelligent Systems and Computing, pp. 112-118, 2022.
- [11] K. Arnold and M. D. Pistilli, "Course signals at purdue: Using learning analytics to increase student success," in Proc. 2<sup>nd</sup> Int. Conf. Om Learning Analytics and Knowledge(LAK), pp. 267-270, 2012.
- [12] J. Kim, Y. Jo, and H. Kim, "Early prediction of student dropout in online courses using learning behaviour data," Computer & Education, vol. 166, pp. 104-123, 2021.
- [13] A. Pena-Ayala, "Educational data mining: A survey and a data mining- based analytics of recent works," Expert Systems with Applications, vol. 41, no. 4, pp. 1432-1462, 2014.
- [14] S. Delen, "A comparative analysis of machine learning techniques for student retention management," Decision Support Systems, vol. 49, no. 4, pp. 498-506, 2010.
- [15] M. N. Quadri and N. Kalyankar, "Dropout prediction in higher education using data mining techniques," International Journal of Computer Applications, vol. 95, no. 13, pp. 24-28, 2014.
- [16] Y. Xing, X. Chen, J. Stein, and M. Marcinkowski, "Temporal prediction of dropout in MOOCs: Reaching the low-hanging fruit through stacking generalization," Computers in Human Behavior, vol. 58, pp. 119-129, 2016.
- [17] F. Marbouti, H. A. Diefes-Dux, and K. Madhavan, "Models for early prediction of at-risk students in a course using standards-based grading," Computer & Education, vol. 103, pp. 1-15, 2016.
- [18] T. Gray and M. Perkins, "Utilixing predictive analytics to identify students at risk of academic failure," Journal of Learning Analytics, vol. 6, no. 2, pp. 87-102, 2019.
- [19] A. K. Verma and S. pal, "Student performance and dropout prediction using machine learning techniques," International Journal of Emerging Technologies in Learning, vol. 15, no. 16, pp. 17-34, 2020.
- [20] L. P. Macfadyen, and Dawson, "Mining LMS data to develop an early warning system for educators: A proof of concept," Computer & Education, vol. 54, no. 2, pp. 588-599, 2010.