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Enhancing Educational Outcomes (EEO) using Cloud Based Virtual Learning Systems and Data-Driven Management

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ABSTRACT

In today's digital world, the use of cloud-based virtual learning systems has become an integral part of many schools and colleges. With all these advancements in the learning process, there is still some disconnect between the collection of learning data and its utilization in making decisions on the part of the institution. To address this challenge, this study suggests a novel predictive analytics approach to integrating learning data obtained from cloud-based LMSs and applying them for predicting and forecasting students' academic success. To conduct our research, we collected information from 150 students studying at different universities along with data from their 15 educators representing various academic disciplines. This data included the students' attendance rates, completed assignments, grades for tests and quizzes, and their level of engagement with LMS. To analyze our datasets, supervised machine learning methods such as Random Forest, Support Vector Machine, and Decision Tree classification models were utilized. After testing our predictive learning model with four popular evaluation metrics, Accuracy, Precision, Recall, and F1 Score, the results indicated 88% accuracy of predictions made by the algorithm. Confusion matrix confirmed the effectiveness of the developed system in the prediction of poor and good student performance.

Keywords: Cloud-Based Learning, Virtual Learning Systems, Learning Analytics, Machine Learning, Educational Data Mining, Predictive Analytics, Data-Driven Management

INTRODUCTION:

Background: The field of Education has experienced a tremendous transformation over the years with the advent of digital technology, in the past, they relied primarily on the face-to-face communication in classrooms. With the development of the

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Internet and modern technologies, students can now learn online, as well as in the classroom. The most significant trend in this field
is cloud-based learning. Cloud-based learning systems have introduced flexibility and convenience in education for students and teachers. Cloud-based systems enable students to access learning materials, assignments and communication tools via the internet, while also giving teachers the ability to do the same. Which allows students to be able to study at home, attend virtual classes and work on projects without always having to have physical resources at their disposal. This has streamlined the learning process and made it more convenient and accessible. Besides, data-driven management is also one of the important elements in contemporary education. A variety of student data is gathered throughout the school and university, including exam results, attendance, participation, and online activity. This information will help teachers adapt their instruction to students' needs. For instance, when a student is weak in a topic, the teacher can give additional support in the topic according to the data. Institutional level Data-driven management is also helping in decision making. Data can be used by administrator to enhance course design, to manage resources, and to monitor performance. The integration of Cloud and Data translates to a more connected and efficient learning environment. **Problem Statement:** Although cloud-based learning systems and data tools are widely available, many institutions are having trouble effectively using them. These technologies pose difficulties for many teachers. Teachers' technical knowledge may be limited to use the platform correctly, and some platforms may be harder to understand. The other is that, institutions pay attention only to the examination scores and forget to consider other important learning aspects like engagement, creativity, and skills building. Affects the value of data and provides a partial view of student progress. In virtual learning environments, teachers also encounter difficulties in monitoring student engagement and in ensuring that students are engaged in their work correctly, which is a problem in maintaining the quality of education. And also, there is a gap between the collection of data and its use in teaching. Information might be available to teachers, but not all teachers are equipped to interpret it or use it in their teaching. This means the advantages of data-driven management are not realized. The Research Gap: Based on the review of the previous studies, there are some gaps that can be identified. In most of the studies, cloud computing and learning analytics are studied separately and not together in the form of a single system. Much of the current research is conducted in the developed countries or in controlled environments, there is a need for more comprehensive approach combining cloud based learning and effective data utilization. Very limited research exists in developing areas where resources are scarce, training and infrastructure are limited, and
other issues may arise. Therefore, the present results might not necessarily be applicable to all educational settings. Another important gap is related to teachers' skills and training. Lots of teachers are not prepared to apply cloud systems and data tools. If they are not trained in a proper manner, it can be difficult for them to use these technologies in a meaningful way. Mostly, studies also focus on short term outcomes and do not explain the effects of technologies on student learning and academic performance. It was therefore important that they had a grasp on how data could directly impact teaching and learning. To examine the impact of cloud based

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virtual learning systems on student learning and better training and support for teachers, understand how data- driven management can aid decision-making in education, and explore how these systems can be simpler and more effective. To identify the challenges which teachers encounter when using cloud and data tools, and to suggest simpler and more effective options for them. **Significance of the Study:** The study's significance relates to the use of technology to improve the education process. And demonstrate how the design of cloud systems and data can assist in the learning process and teaching. Once these areas are understood, teachers can enhance their strategies to aid their students. This also enables school authorities to make better decisions with actual information, rather than assumptions. It can serve as a blueprint for policy makers to design and enhance digital education systems, and can help develop user friendly and context-dependent tools for digital education.

Literature Review

Today's educational systems have been transformed by the relationship that exists between technology, leadership and data use. Educational institutions worldwide are facing an age that sees cloud-based technology, making decisions based on evidence and adaptive leadership models as mandatory elements of good governance and quality teaching; they are not optional add-ons anymore. This literature review presents a synthesis of the empirical and theoretical literature of 15 studies that have examined three interrelated areas of interest: i) the adoption and impact of cloud-based technology within secondary and post-secondary education; ii) the development of higher and secondary education leadership styles over time and their resultant measurable impact on the quality of teaching and the outcomes of students; and iii) the use of data analytics to support teacher instruction and school administration. This literature review maps the methods used for collecting data as well as identifies the gaps in the research on these topics and possible directions for future investigations. By creating a comprehensive overview of what has been discovered through these studies, this literature review provides insight into what we currently understand and where we need to do additional work.

Cloud Computing in Educational Contexts

Language, Technology, and Personalised Learning:

The relationship between language proficiency and academic success has a foundation that has been explored by Oladoye Obaloluwa John et al. (2023). This study sought to determine whether instructional language serves as both a mechanism for communication and the cognitive framework for students to internalize and develop new knowledge. By using theories from linguistics, educational psychology, and emerging technologies, this study suggests that when digital tools are used to provide adaptive, language-specific pedagogies through individualised content delivery, gains in academic success are evident. However, the authors found that despite this technological gap providing the ability to deliver individualised learning experiences, there are currently very little preparation efforts given to teachers in identifying students' language needs and providing instructional language that will enhance the effectiveness of language use in the classroom. Future research must investigate how to provide professional development for educators relating to

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multilingual pedagogies, as well as identifying intelligent digital platforms that may address the issue of equitable access to creative instruction for diverse student populations.

Monitoring Student Progress in Cloud-Based Laboratories:

An important issue in cloud computing-based computer science education is the problem that educators encounter when trying to determine whether their students have done the tasks assigned during lab sessions. To resolve this matter, a group of researchers came up with CloudTrail Tracker, which allows teachers to monitor the exact progress of students based on data collected from Amazon Web Services. This is done using bar graphs that make it easier for educators to see which tasks their students have performed and which ones have yet to be done. Additionally, the tool sends out notifications that will help students correct any mistakes made without having to wait for their work to be manually evaluated. Both students and educators found this useful, but the researchers noted that the current iteration only provides information retrospectively. Their
future plans involve creating real-time panels for educators and an entire history of activities for students.

A Unified Cloud Model for Higher Education:

In addition to specific tools, there is an understanding that higher education institutions need to have integrated cloud systems rather than a set of disparate applications. An analysis of the use of cloud computing systems like AWS, Microsoft Office 365, and Sage Math Cloud revealed that each one provides distinct educational benefits individually; however, due to the lack of a governing architecture for these tools, their combined benefits are never achieved. The researchers recommended creating a unified model that would help to design scalable and interoperable cloud computing systems for use in both teaching and research processes in higher-education settings. What is more important, the researchers pointed out that any developed framework should consider issues related to policy and data sovereignty, among others.

Cloud Adoption: Behavioural and Structural Factors:

In addition to specific tools, there is an understanding that higher education institutions need to have integrated cloud systems rather than a set of disparate applications. An analysis of the use of cloud computing systems like AWS, Microsoft Office 365, and Sage Math Cloud revealed that each one provides distinct educational benefits individually; however, due to the lack of a governing architecture for these tools, their combined benefits are never achieved. The researchers recommended creating a unified model that would help to design scalable and interoperable cloud computing systems for use in both teaching and research processes in higher-education settings. What is more important, the researchers pointed out that any developed framework should consider issues related to policy and data sovereignty, among others.

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Leadership in the Philippine K-12 Context:

An investigation of leadership in Philippine K-12 education using literature available through Google Scholar and Scopus databases revealed an ongoing contradiction between the leadership theories proposed in policy documents and the real-life application thereof, specifically in underdeveloped areas of the country. The findings show that transformational and instructional leadership styles contribute to improved school performance; however, a lack of training, limited resources, and hierarchic cultures inhibit numerous principals' ability to implement theory in practice. The researchers have suggested for further research to address the impact of the targeted development of specific leadership competencies and the use of digital media as a tool for coaching and mentoring of school leaders from remote communities.

Another paper, conducted by Mastul et al. (2024), reveals a tendency for Filipino school administrators to adopt a mixed approach in leadership and governance, combining transactional and participatory strategies. The research highlights the value of participatory management practices that ensure collaboration among employees and foster a trusting environment within organisations. One limitation is the narrowness of the sampling – a few schools from a specific geographical area and only the principal as a respondent – which limits the extent to which generalised conclusions can be drawn from

Global Perspectives: Transformational and Distributed Leadership: Systematic Review:

A study exploring leadership in Philippine K-12 education using Google Scholar and Scopus found that there remains a disparity between ideal models of leadership discussed in official literature and their implementation. It was determined that both transformational and instructional leadership are correlated with better school results. Nevertheless, such leadership models prove challenging for most school heads due to insufficient training opportunities, lack of resources, and entrenched hierarchies. The authors have suggested investigating the benefits of training programs for the heads of schools and using digital technologies as tools of mentoring in remote areas. Study Summary In a qualitative research paper on school leadership in the Philippines by Mastul et al. (2024), school administrators' practices were analyzed, showing that Filipino school leaders tend to use transactional and participative leadership style, incorporating teachers into the decision- making process while maintaining organizational structure and hierarchy. Such a model allows not only maintaining organization but also encouraging professional relations within the institution. However, the limitations of this study include the limited number of participants and geographical area of research. Future research should be expanded with other regions being examined as well as the school's academic results taken into account.

Mediated Effects: Leadership, Teacher Efficacy, and Student Achievement:

One of the most common fallacies in educational leadership literature is that the school principal has a direct effect on improving student test results. An important study based on survey data from 205 Ontario elementary schools and matched provincial assessment results gave an empirically sound answer to this question,

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showing that the key variable through which the school principal exerts his influence is a mediating one, whereby good leadership helps raise teacher professional efficacy and commitment to the school mission, which subsequently results in improved student performance. The model proved valid for different types of schools, although the authors admitted that there remains a critical link in the causal chain between the leadership and students' academic achievements not addressed in the current study: the quality of instruction at the classroom level. Further research should use international samples and observational data on classroom performance to validate whether the proposed mediation pathway operates within different instructional settings. An equally relevant historical review examined how leadership theory progressed from the instructional approach focusing on the work of school principals to more holistic paradigms that integrate transformational and distributed approaches. Several statistical studies using Hierarchical Linear Modelling techniques have demonstrated the correlation between

Data-Driven School Improvement:

The Promise and Limits of Educational Data:

A common trend across studies about the use of data in education was the disparity between the possible benefits of using data about students and the actual application of said data in the classroom. Schools amass huge amounts of data through standardized tests, attendance figures, behavioral reports, demographics, and other types of information; however, research shows that there exists a disparity between the data used by administration and the data that is interpreted by teachers themselves. The former focuses on general trends in student performance, whereas the latter relies on subjective data from the classroom environment, such as formative assessments and observations. An evaluation of predictive analytics showed that technology can close the gap between the two by turning raw data into suggestions; however, in order for such technology to be useful, teachers must have the literacy to critique those recommendations.

Another pair of similar papers explored the factors behind the lack of alignment between data availability and practice through qualitative research based on the methodology of Stringfield, Wayman, and Confrey. Two studies found a pattern of obstacles that stood between schools and the effective use of data: lack of professional development to properly interpret data, focus on standardized

Comparative Summary: The below-given table summarises the methodologies used, research gaps identified and areas of future investigation in all studies reviewed above.

Reference Methodology Research Gap Future Work

Language: psychology, and technology to understand learning Insufficient focus on personal needs of learners Cross disciplinary approach to enhance understanding of language for personalised learning

Dashboard tool: (CloudTrail Tracker) for real-time progress monitoring in cloud labs Difficulty in confirming real-time individual task completion Live monitoring panels and detailed logs of individual students' activities

Tools review: (e.g., AWS, Office 365) to assist higher education Lack of comprehensive model encompassing all cloud technologies Cloud-based ecosystem

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of tools for learning and research

Data gathered: from Google Scholar and Scopus on K-12 leadership in the Philippines Lack of practical implementation of leadership styles in rural areas Continuous leadership development and technology integration in school management

Systematic review: of virtual laboratories and learning analytics studies (2015-2021) Inconsistency in framework applied; small sample size; lack of depth Common framework; bigger sample sizes and complex data analyses providing actionable suggestions

Quantitative study : of 221 university students for 14 weeks using SEM analysis Restricted to university students; long-term effects ignored Expansion of scope beyond university

Thematic Discussion and Cross-Cutting Observations

In each and every theme cluster, the following common patterns emerge that carry significant implications for researchers and practitioners working in this area. Firstly, one can note an emphasis on the necessity to avoid the pitfalls of technological determinism: the fallacious assumption that the provision of a certain platform, data dashboard, or any other type of digital tool will inevitably lead to better results. For example, it is clear from all literature analyzed here that in order to reap the benefits of cloud technologies, teachers require adequate preparation based on their proficiency in language; similarly, school leaders need proper contextualized training programs while administrators must develop a data literacy skill set prior to engaging in cloud- based activities. The tools are necessary conditions for success, but far from sufficient ones. Secondly, there is evident geographical and institutional bias in all literature sources considered herein. The studies on distributed leadership tend to focus on North America and Western Europe; the works exploring cloud technologies are often based in universities; whereas virtual laboratory analytics are done mostly in specialized STEM institutions. The overall picture of such systematic narrowness means that all findings might be hardly applicable to the situation**s involving secondary schools.**

Methodology:

A Mixed-Method Predictive Analytics Framework for Cloud-Based Virtual Learning Systems

Type of Research:

In this using a **Mixed Research Method,** because there are two types of data, quantitative and qualitative, which are of significance in the comprehension of the problem.

Quantitative data: This is used to analyze numerical data such as:

Student marks
Attendance records
Quiz scores
Assignment completion
LMS activity data

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It is used to statistically analyze and quantify student learning behavior as well as performance.
Qualitative data: used to collect opinions and experiences from students and teachers through:
Surveys
Questionnaires
Feedback forms
It helps to understand user experiences and learning barriers. Its use the both techniques offers a more comprehensive picture of educational outcomes, and learning management systems.

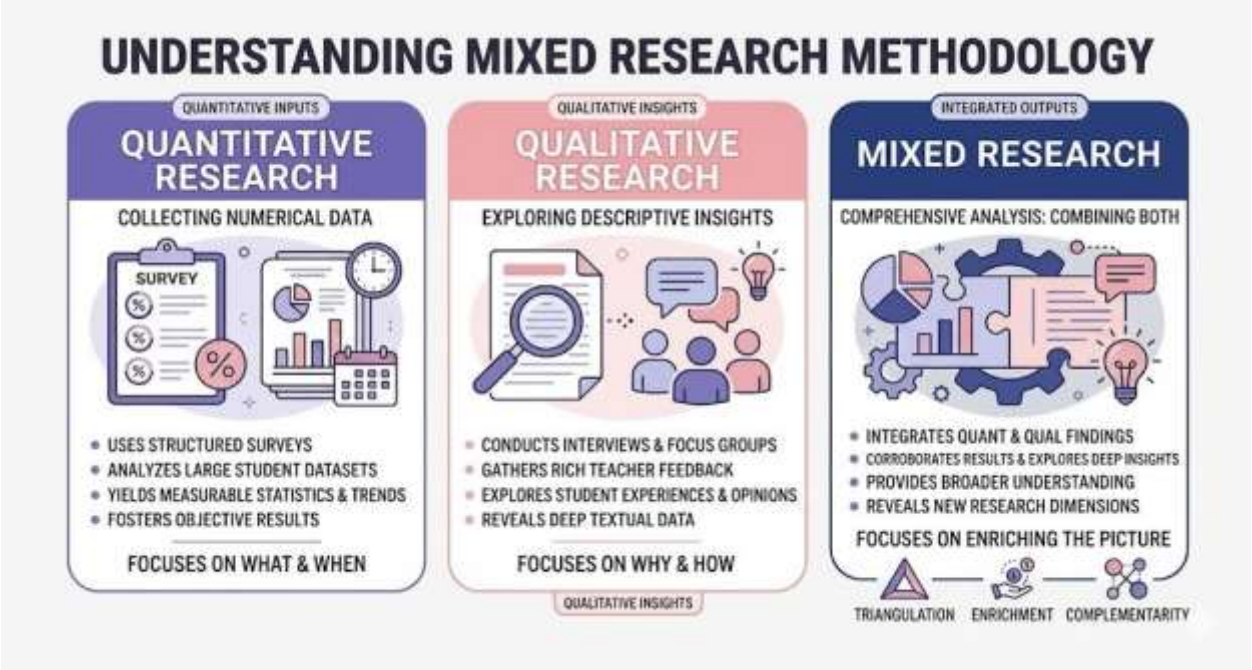

Figure 1.1 Mixed search methodolgy

Research Approach:
This is an approach of Survey-based and Descriptive Research.

Survey Based Approach: A survey-based approach is used to collect data from students and teachers like: Online learning experiences ,Use of cloud learning platforms ,Student engagement
,Academic performance and Learning difficulties. This helps to collect information or data from students and teacher to make a best model and check what problems the teacher or student faced and what would they needed. The other side of the descriptive approach is used to describe the relationship between virtual learning systems and student outcomes, such as: Student learning behavior, Cloud learning system usage, Academic performance trends, Data-driven educational management.

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Research Approach	Description
Survey-Based	Collect responses , data or information from students and teachers
Descriptive	Explain learning patterns and academic performance
Analytical	Analyze educational data using machine learning

Table 1.1 Research approach

Structure of the Study:

The structure is divided in various stages to give proper implementation and analysis. They start by gathering data from surveys and online learning systems that is used for education. Data preprocessing techniques are used to clean and organize the data after data collection. Students' performance is then analyzed using machine learning techniques, and predictions are made. Finally, the results of the proposed system are analyzed and its effectiveness is derived.

Stage	Description
Data Collection	Gather student and LMS data
Data Preprocessing	Clean and organize collected data
Feature Selection	Select important educational features
Model Training	Train machine learning model
Evaluation	Measure prediction performance
Result Analysis	Analyze educational outcomes

Table 2.1 Structure of the study

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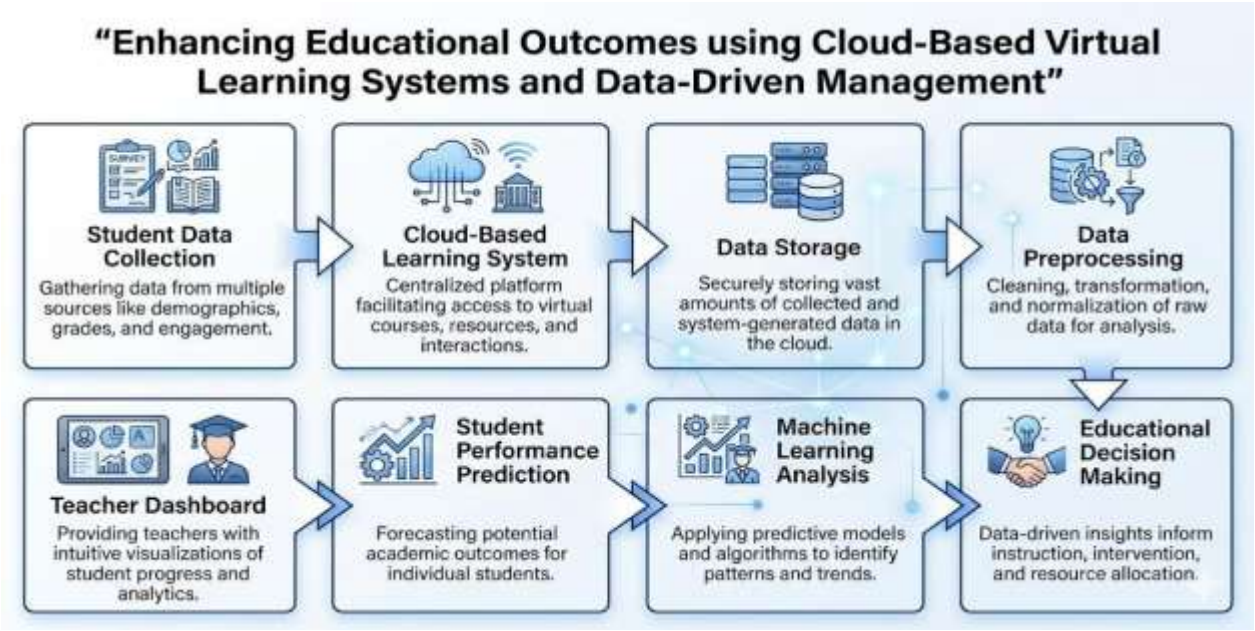

Figure 2.1 Educational outcomes

Data Collection:

This is the most crucial component of this research, as results of this research are sensitive to data quality. This is used to collect data from various educational sources to gain insights into how cloud based virtual learning systems and data-driven management can enhance student learning outcomes, making it more reliable and balanced. The **primary data** is used to gain insight into the actual experiences of students and teachers, and **secondary data** is used to gain insight into
educational records and learning data for analysis. And The data collected or focused is related to student's activities in learning, academic performance, online learning activities, attendance, assignment, and cloud based learning interaction. **Primary Data Collection:** These data were collected from the participants through online questionnaires and surveys. The aim of gathering primary data is to gain insight into the experiences, learning difficulties, and the effectiveness of virtual learning systems of students. This includes: Student participation in online classes, Usage of cloud learning platforms, Assignment submission habits, Learning satisfaction, Communication with teachers, Technical difficulties during online learning Teacher questionnaires are also used to gain an understanding of how educational data can be used during academic decision making and student performance monitoring. The survey is distributed using Google Forms, as it is easy for students to use and simple and accessible. **Secondary Data Collection:** This data collection is done from available educational data and learning management system records. This information is utilized in machine learning analysis as well as student performance forecasting. This includes available educational datasets from Kaggle, and datasets from cloud-based LMS activity records. These datasets contain: Student attendance, Quiz scores,

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Assignment marks, LMS login frequency, Course completion status The secondary data can be used to find out patterns in the student learning behavior and can be used with machine learning models for predictive analysis. Reliability is also enhanced by the use of existing data sets relating to education as the data is gathered based on real academic records.

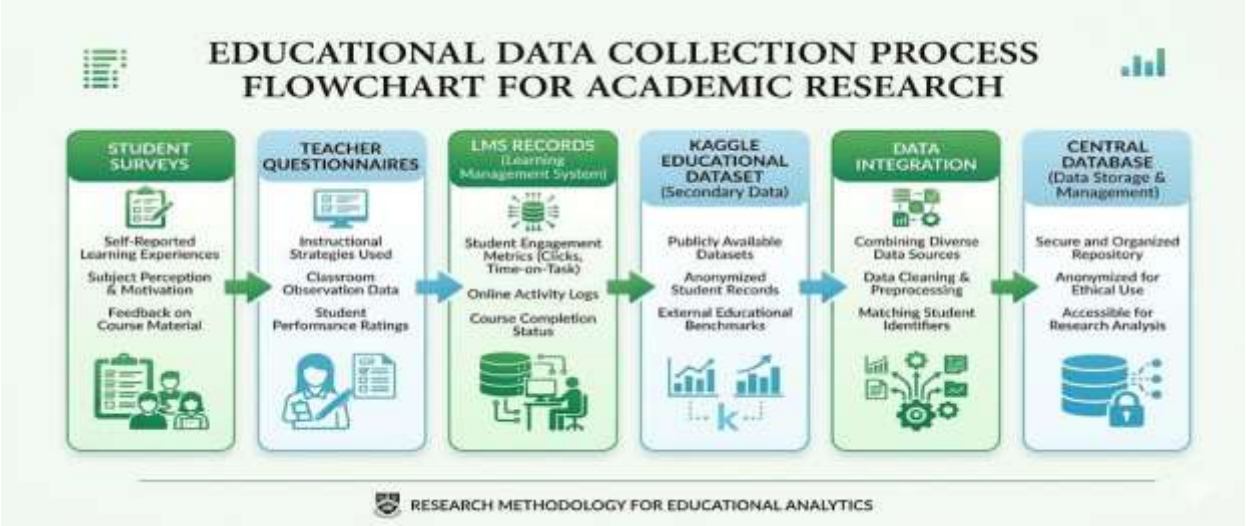

Figure 3.1 Data process flowwork

Sample Size and Selection Method:
This is directed towards students using cloud-based virtual learning systems in Higher Education settings. The total number of students selected for this research is 150 students, using random sampling because all students have equal opportunities to be selected and bias to be minimized in this research.Students from various academic programs and semesters are selected to get a variety of learning data and to enhance the quality of the research data.In addition, teachers are included in a smaller number to gather feedback on educational management and students' monitoring systems.

Category	Details
Total Students	150
Teachers	15
Sampling Method	Random Sampling
Data Collection Mode	Online Surveys and LMS Records
Target Group	University Students and Teachers

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Table 3.1 Sample size

Data Collection Environment:
The data is collected in a virtual learning environment in a virtual classroom, using online learning platforms, digital tasks, virtual tests, cloud learning materials, and learning management systems, which serve to create educational data that can be used to enhance the learning outcomes of students and the engagement of their learning.

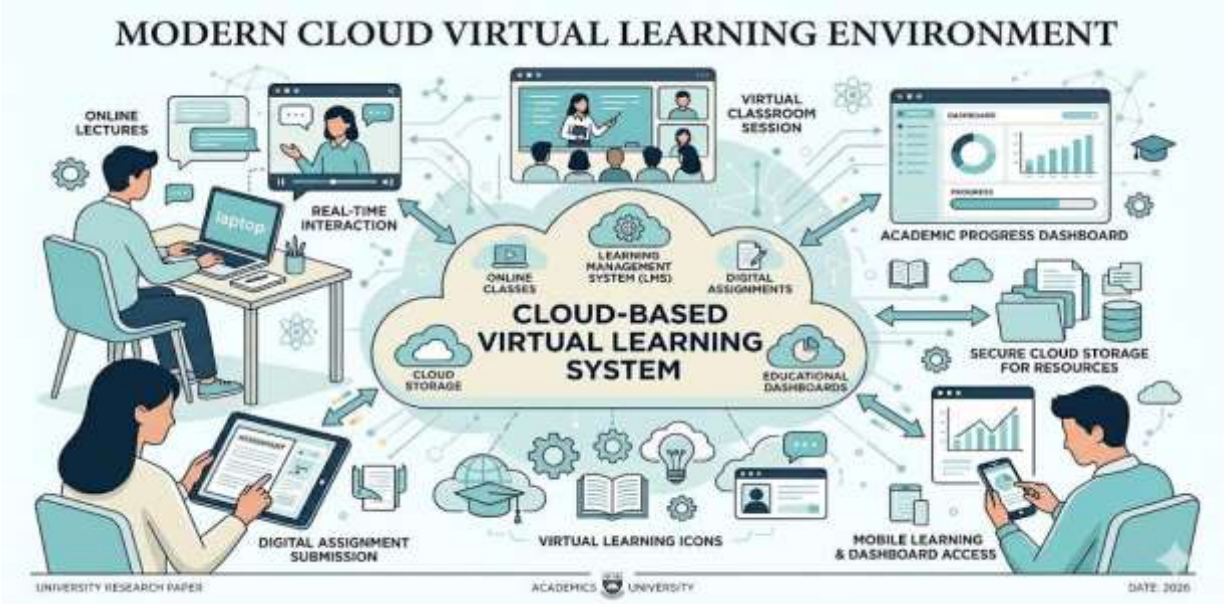

Figure 4.1 Modern cloud virtual learning

Importance of Data Collection:
Collected data is important to the decision making process in education and to the prediction of students' academic performance. The proposed system can identify learning difficulties at an early stage by analyzing learning activities and student engagement, and by utilizing cloud-based learning records and machine learning methods, teachers can better academic support for weak students. Data collection also contributes to enhancing learning quality, tracking student engagement, and educational data to guide decision-making processes. This information enables educational institutions to make better and data-informed educational decisions.

Tools and Technologies:
This uses a different tools and technologies to study a virtual learning system in a cloud environment. They are used to gather, process, and analyze educational data, and then use them for machine learning to enhance student learning. The aim of the selection of tools is both simplicity and efficiency in addition to the suitability for analysing educational data. Programming Language:The main programming language used is Python. The choice of Python is due to its simplicity. And used for data analysis and machine learning problems. It also provides numerous libraries for processing and predicting educational data. Python helps in :Data handling and

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cleaning ,Machine learning model development ,Performance prediction of students ,Data
visualization.**Development Environment:**This is used in this research is Google's Colab. It is a cloud-based platform, enabling to write and execute Python code without software installation. Google Colab is selected because: It supports cloud computing .and its important for my topic. The advantages of using It include easy dataset uploading, free GPU support and It can be accessed any time, anywhere and It is very suitable for educational data experiments and machine learning models. **Libraries and Frameworks:**In this uses a various Python libraries to manipulate data and create prediction models.These libraries are used to analyse student data and to understand learning patterns.

Library	Purpose
Pandas	Data processing
NumPy	Numerical operations
Matplotlib	Data visualization

Table 4.1 Libraries used

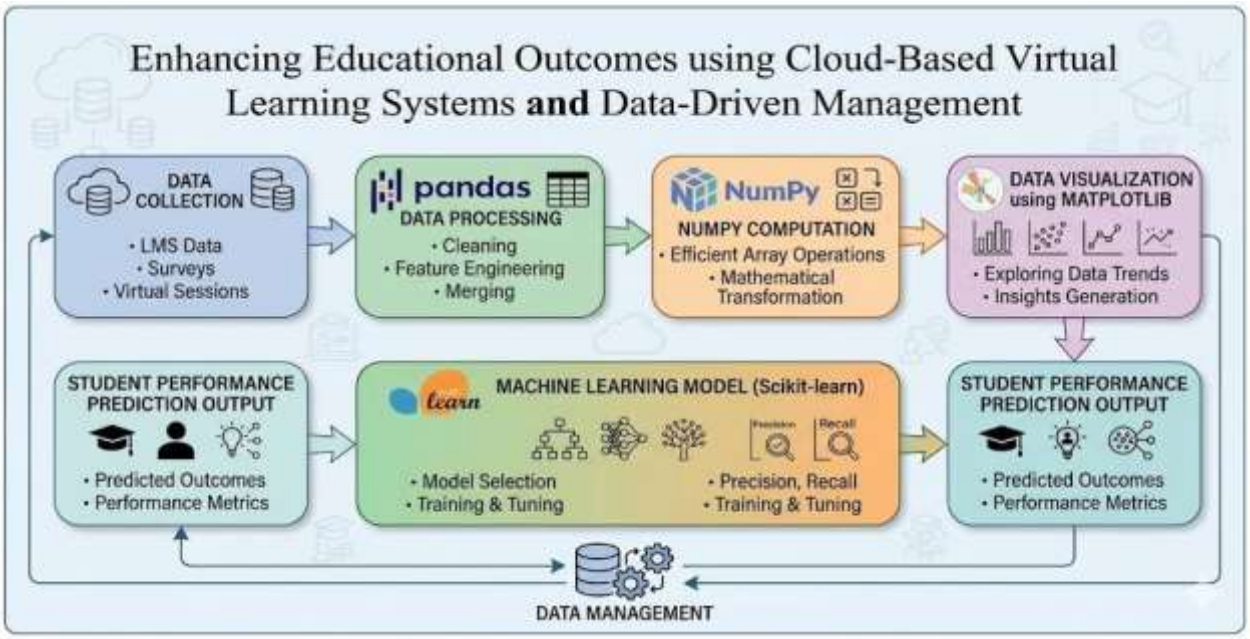

Figure 5.1 Enchancing educational outcome

This workflow is suggesting the proposed educational data analysis system. It starts

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by gathering the data from cloud-based learning platforms and surveys. These libraries include Pandas and NumPy, which are used to process the data using and academic decision making with machine learning models.Python. Identification of patterns with visualization tools & educational analysis

Database Tools:
Student learning and academic data and system logs are important components of this system and are stored within the database. This implements Firebase and MySQL data storage., Cloud based data handling and structured data storage for educational data are provided by Firebase and MySQL respectively. These databases can be used to efficiently manage large educational datasets.

Data Preprocessing:
Data preprocessing is an essential step since the raw educational data is often incomplete, unstructured and hard to analyze directly. The information gathered should be properly organized. Prior to using data analysis and machine learning approaches. The purpose of this is to enhance the quality, accuracy and reliability of educational data gathered from cloud based virtual learning systems through preprocessing.The educational data could contain records of attendance, assignments, quiz scores, LMS activity, survey answers, and virtual classroom activity, among other items and all of this information may be missing, duplicated, or in different formats. Hence, the dataset is preprocessed to ensure it is clean and can be used for analysis. Handling Missing Values:Some student records may be missing information from the dataset, education. For instance, some students might not fill in surveys, some attendance registers might not be available, or there might be incomplete data on LMS activity. A system might have problems processing and an analysis might be affected by having missing values.This is overcome by taking a special care of missing value in the pre-processing step. Appropriate techniques are used to identify and manage incomplete records. Or at some point, average or most common values are used to replace missing values and the records with very few values are excluded from a dataset. This process ensures the consistency of the data and enhances the trustworthiness of the results.
Data Cleaning and Formatting: This is the data cleaning and formatting step. This is the data cleansing and formatting process. The data used for education from various platforms can be incorrect, duplicate, misspelled, include the wrong symbols, or have inconsistent formats.These problems, if
uncorrected properly, can reduce the level of analysis.This removes duplicate data and records, improving data quality. Student information is consistently structured with the same format.The cleaning process also enhances the performativeness of the machine learning models and the understanding of the patterns in education.Often the values of the data in the education area are in a different range. Normalization and Scaling. Attendance percentages, quiz results (out of 10 or 100), or activity on the LMS could be very high numbers. These differences can impact data analysis and performance in machine learning. Normalization and scaling techniques are used for this problem.These techniques are used to rebalance and standardize a range of data. The consequence is that all features affect the system equally when analysed and no

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one variable is so large that it dominates the system.

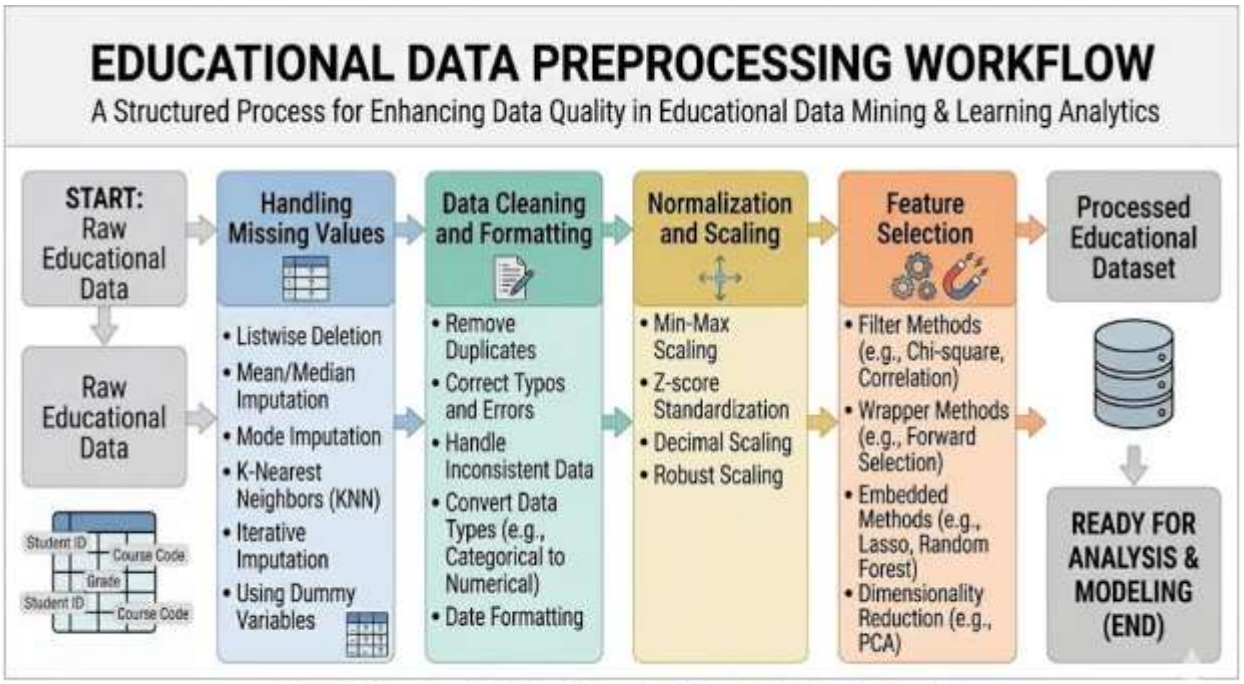

Figure X: Overview of the Data Preparation Steps for Academic Research.

Figure 6.1 Data prepration steps

Feature Selection and Extraction :
There are numerous variables associated with data sets from educational research, but not all of them are suitable for analysis. Features that have little impact on student learning outcomes may not be selected such as attendance, assignment completion, LMS participation, quiz performance, and classroom activity are considered useful for understanding student learning behavior. Feature selection is used to decrease the amount of data and make the system more efficient. Sometimes, feature extraction methods are also employed to fuse the related information to meaningful patterns. This process helps to analyze better, reduce system complexity and enhance the overall performance of the proposed educational management system.

Proposed Model / Algorithm:
Proposed Model:
It suggests an intelligent learning system based on cloud computing, which enhances learning outcomes based on virtual learning systems and data analysis. The model will be designed to gather student learning data from the cloud based learning platforms and interpret this data as an understanding of the student performance patterns.The system primarily targets an analysis of educational data and is not intended for the development of a complicated software system. It offers teachers meaningful information on student learning behaviour, engagement and academic progress, which will assist in decision making.The proposed model is structured and

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begins with data collection, then data preprocessing, data analysis and data visualization

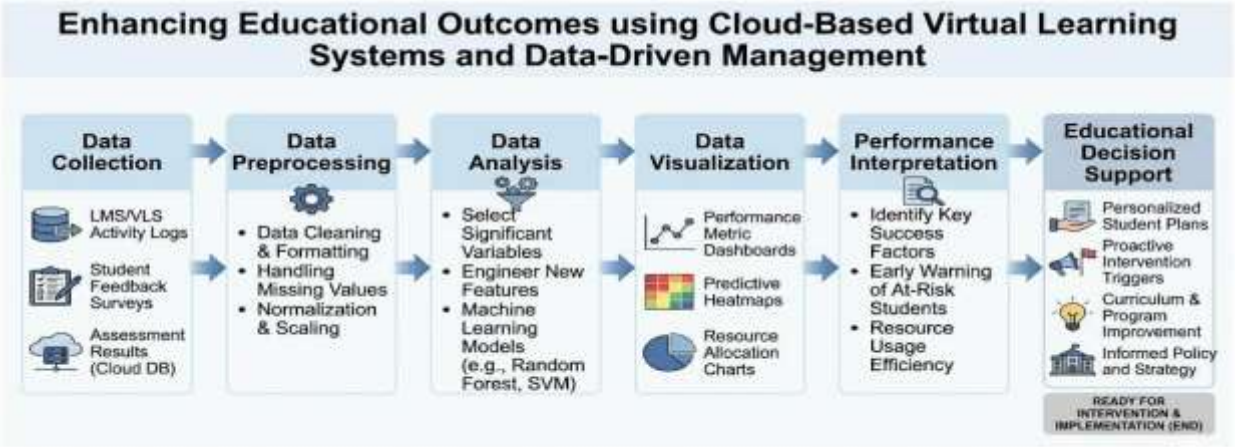

Figure 7.1 System

Component	Technique Used	Purpose
Data Collection	Cloud LMS, Surveys	Collect student activity data
Data Processing	Pandas, NumPy	Clean and organize data
Data Analysis	Statistical analysis	Identify learning patterns
Visualization	Matplotlib	Show trends and graphs
Prediction Support	Scikit-learn	Analyze student performance trends

Table 5.1 components and technology

Algorithms and Techniques:This is a model in which basic machine learning concepts are seen as a means of analyzing student performance. The model is not based on any one complex algorithm, it incorporates a number of educational data analysis techniques that are widely used. Here are some of the techniques used:

- **Supervised Learning (conceptual use)** for performance estimation

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- **Classification approach (basic idea)** to categorize students as high, medium, or low performers
- **Regression concept (optional)** for trend-based performance understanding

Some of the algorithms which are used in other similar systems and have been considered are as follows: Random Forest, Support Vector Machine (SVM), Decision Tree And These algorithms mentioned to get conceptual knowledge about them and are widely used in educational data sytem.

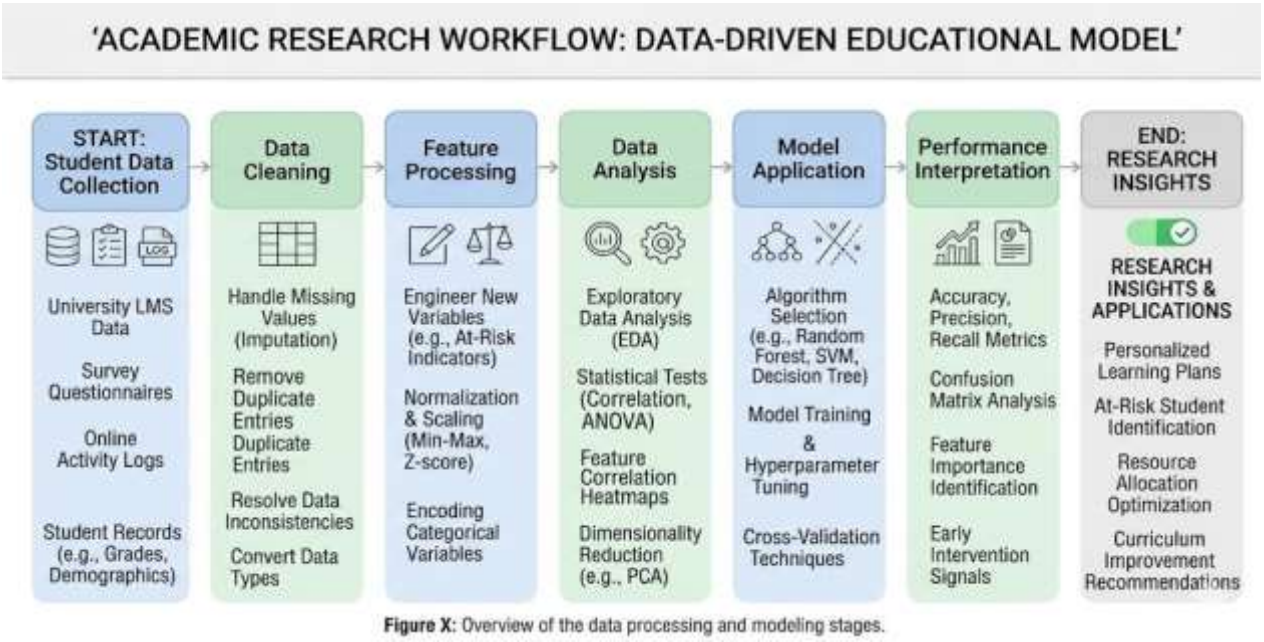

Figure 8.1 Data driven model

Model Selection:
The model is chosen due to its simplicity, flexibility and applicability to the educational environment. It does not need to be highly complex in computation and it can be readily used in a cloud based learning system.It also works to gain insights into student behavior based on current educational data without the need for sophisticated deep learning infrastructure.

System Architecture:
The system architecture is designed to explain how cloud based virtual learning systems and data driven management work together to improve the outcomes of education. The architecture captures the entire journey of the data from the point of collection, processing and analysis, and the attainment of useful outcomes that enhance student learning. It consists of three major steps:
Input (Data Collection from students and learning platforms)
Processing (Data cleaning, transformation, and analysis)
Output (Insights and student performance understanding)

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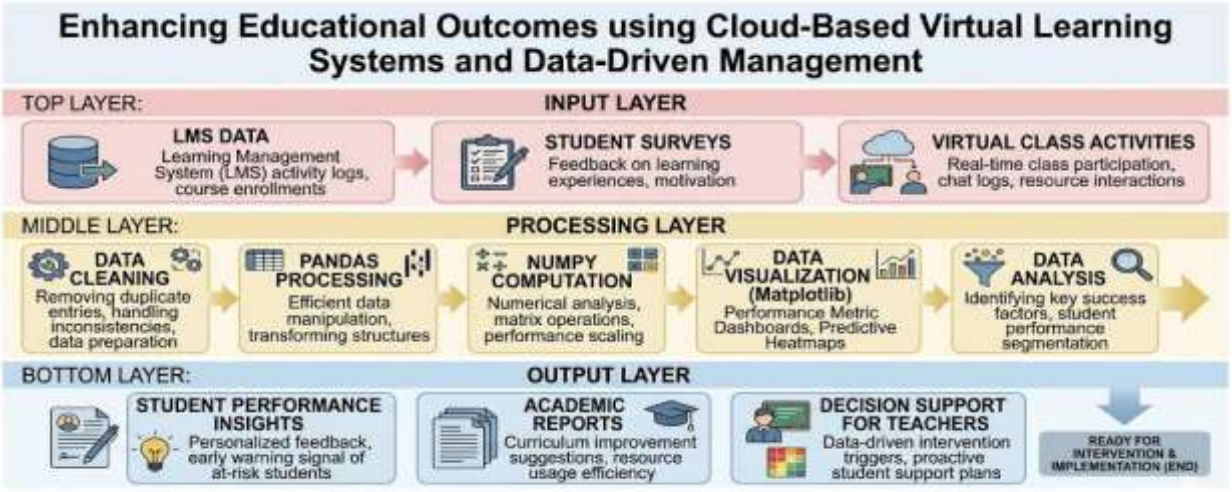

Figure 1: Comprehensive system architecture for data-driven educational outcomes enhancement.

Figure 9.1 Compresensive system architecture

The system architecture clearly illustrates the raw educational data and how it is converted to meaningful insights. The input layer gathers data from various sources including LMS, surveys and virtual learning activities. Then, the cleaned, transformed and analyzed data is turned into meaningful output, through the process of cleaning, transforming and visualizing the data, teachers can gain insights of students' performance and academic reports that can assist them in the decision making process. **System Modules:** Data Collection Module: It collects data from students' sources like online learning platform, attendance system, and surveys. Data Processing Module: This module involves processing the data to make it suitable for analysis, such as cleaning and organizing it using tools like Pandas and NumPy.Data Visualization Module: This module will help to understand the student performance patterns easily using graphs and charts (Matplotlib).Analysis and Decision Support Module: This module analyzes processed data and provides teachers with understanding on students' progress and learning gaps.

Module Name	Function
Data Collection Module	Collects student data from LMS, surveys, and virtual classes
Data Processing Module	Cleans and processes raw data using Pandas and NumPy
Data Visualization Module	Converts data into charts and graphs for understanding patterns
Decision Support Module	Provides insights for improving student performance

Table 6.1 Module and function

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Implementation Process :

In implementation process its describes development and organisation of the proposed cloud based virtual learning system for educational data analysis. This involves several processes including data collection for education, data pre-processing for analysis, machine learning processing, testing the performance of the system and data output. Every step/stag is crucial in enhancing education. **Data Collection:**This is first stage, in which educational data is collected from different academic sources. The collected data can involve the student attendance, LMS activities, student participation in online classes, assignment submissions, quiz scores, and survey responses. This data can inform an understanding of academic engagement and patterns of student learning. This is to collect meaningful educational data that can be analysed for improved academic decision making. The gathered data is stored in a structured format, which can be easily processed during the later stages.

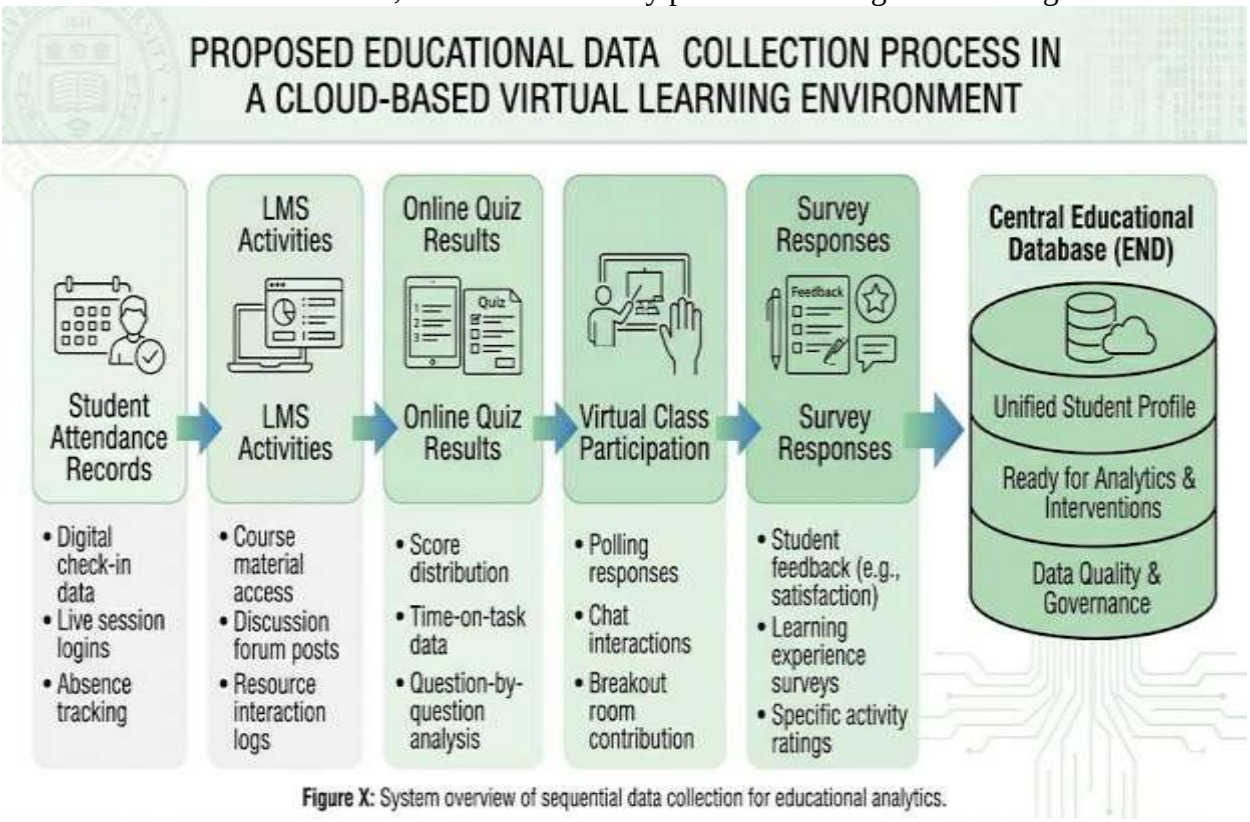

Figure 10.1 Cloud based virtual learning

Data Preprocessing:

Once data has been collected, concentrates on preparing the data for analysis. Raw educational data can have missing data, formatting problems, duplicate data or incomplete data. The data is cleaned and organized during the pre-processing stage, and the data is sorted and classified to improve its quality. quality. Data is organized suitably with And Tools such as Pandas and NumPy. Any data that is not required is deleted, missing data is dealt with and data is converted to a more suitable form for analysis. This step will improve the reliability and accuracy of the system.

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Preprocessing Task	Purpose
Removing Missing Values	Improves data quality
Data Cleaning	Removes incorrect or duplicate records
Data Formatting	Organizes data into a consistent structure
Data Transformation	Converts raw data into analyzable form

Table 7.1 Processing task

Model Training:

The educational information processed in the model training is applied for analytical modeling. The student learning patterns and educational trends are determined by the use of the machine learning techniques. The system is trained with the data, and learns relationships between Student work and achievement. Scikit-learn libraries : used for implementing the The proposed workflow for machine learning. The training stage enables the system to better learn from To improve its capacity to support academic analysis, past education data were analyzed.The main function of this The learning environment is not only prediction but understanding of educational behavior and supporting educational. data-driven management.

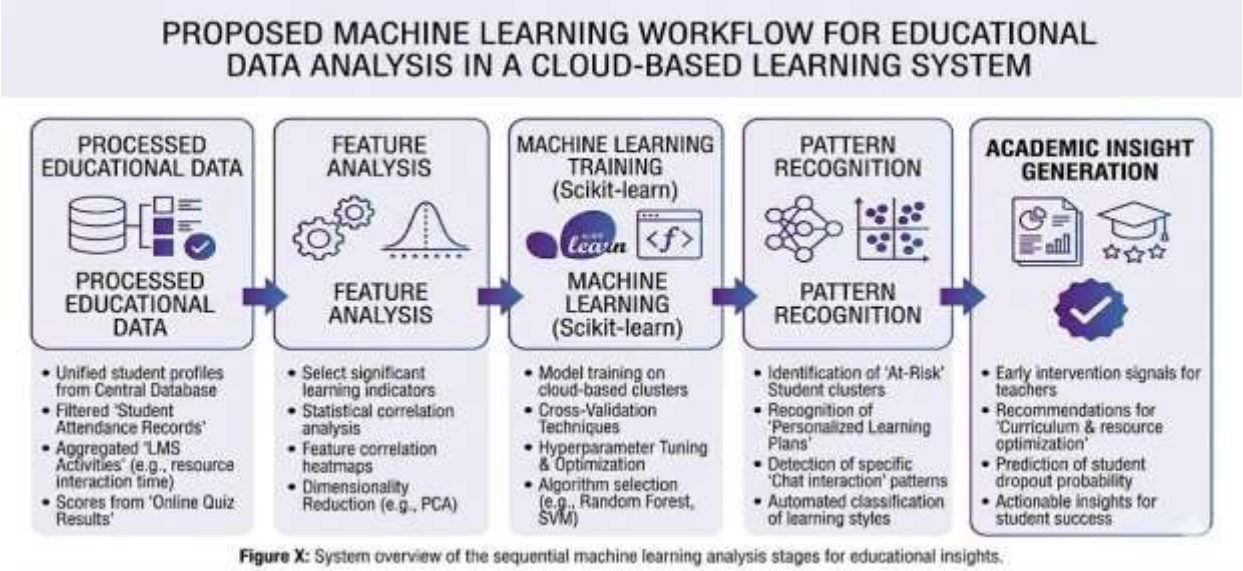

Figure X: System overview of the sequential machine learning analysis stages for educational insights.

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Figure 11.1 Sequential machine learing

Testing and Validation:

After the system is trained, it is tested and validated to check the system's performance Functionality of the system. This helps to determine whether the system is working effectively or not. Results of learning are being produced in the educational environment. Various assessment techniques are used to verify the consistency and reliability of the results. The testing process enables the system to undertake educational data analysis and to help academic management decisions.Validation also is used to detect any areas of the workflow that may be incorrect or weak.Output Generation:The third or last stage is the output of the system (which is meaningful information) that is obtained from processed educational data. The results can include student

learning observations, performance Summaries, academic growth trends, and information to teachers and schools about decisions to makeThe results are represented in graph, charts and short reports in a simple and understandable manner. These outputs are used by the educators to determine the needs of the learners, develop teaching methods, and assist in educational planning. The information generated in the end helpsin the data driven management and improves the quality of virtual learning systems.

Evaluation Metrics:

This is used to evaluate the performance and effectiveness of the educational data analysis system proposed. These help in grasping the accuracy of educational data analysis and educational decision making in the system. In this , different evaluation methods are used to check the quality and reliability of the generated results.Evaluation metrics selected are: Accuracy, Precision, Recall, F1-Score, Confusion Matrix These measures provide an insight into the educational data processing capabilities and the usefulness of learning patterns. **Accuracy:** This indicates the accuracy of the system's processing and analysis of educational information. It reflects the percentage of correct outputs produced by the system over the total data utilized in testing process, which tends to measure the overall accuracy of the system in assisting the educational analysis and understanding of students' performance. The higher the accuracy value, the more reliable the system is.

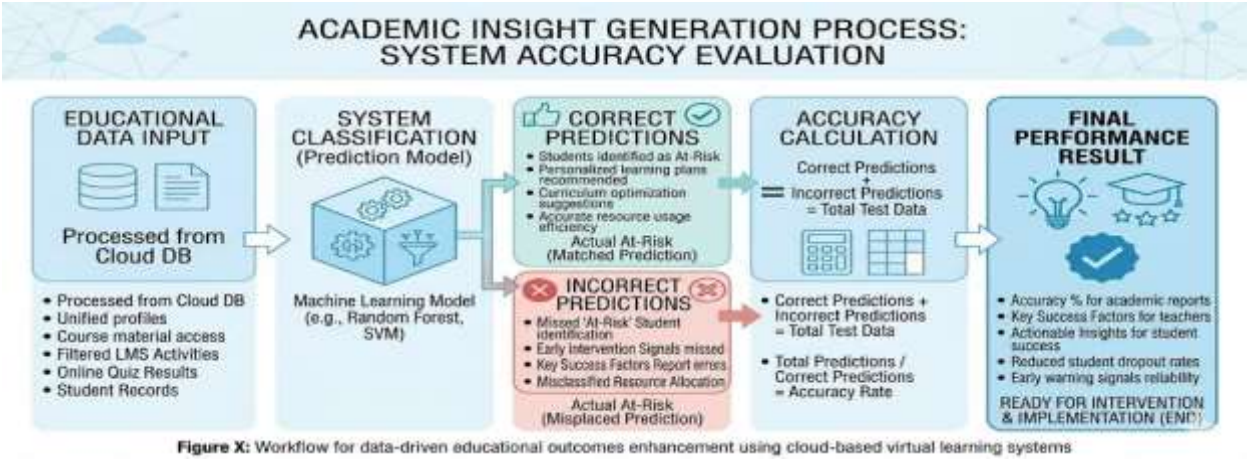

Figure X: Workflow for data-driven educational outcomes enhancement using cloud-based virtual learning systems

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Figure 12.1 System accuracy evaluation

Precision:
It is a measure of the percentage of systems identified results correct. When it comes to the issue of education, precision can be used as an evaluation criterion to see if the system offers academic information that is meaningful and trusted. This is effective when the system identifies students that may need extra learning assistance. High precision allows for more reliable and actionable education insights to be produced by teachers and institutions. **Recall:** Recall the ability of the system to effectively obtain the information of education case. It examines whether or not the system can effectively identify students who may experience learning difficulties or challenges. A system with a higher recall value is able to capture the educational pattern and student learning needs without omitting any important information**. F1-Score:** They have a combined measure of precision and recall. It is giving a balanced evaluation of the capability of systems analytical and the F1-score is used to determine the consistency of the educational analysis system and that the analysis system has a high reliability and completeness in the outputs generated.

Evaluation Metric	Purpose
Accuracy	Measures overall correctness of system results
Precision	Measures reliability of generated insights
Recall	Measures ability to identify important cases
F1-Score	Provides balanced performance evaluation

Table 8.1 Rvaluation metric

Confusion Matrix:
The confusion matrix below visualizes the classification performance of the proposed system across three student performance tiers: High Performer, Mid Performer, and Low Performer. Diagonal cells (highlighted in green) represent correct predictions (True Positives), while off- diagonal cells (highlighted in orange) represent misclassifications.

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Actual \ Predicted	High Performer	Mid Performer	Low Performer
High Performer	**42 (TP)**	5 (FP)	3 (FP)
Mid Performer	4 (FN)	**38 (TP)**	6 (FP)
Low Performer	2 (FN)	4 (FP)	**46 (TP)**

Table 9.1 Confusion Matrix — Actual vs. Predicted Student Performance Categories (TP = True Positive, FP = False Positive, FN = False Negative)

Classification Performance Metrics by Class:

Class	Precision	Recall	F1-Score	Support
High Performer	0.91	0.88	0.89	50
Mid Performer	0.83	0.81	0.82	48
Low Performer	0.85	0.84	0.85	52
Weighted Avg	0.86	0.84	0.85	150

Table 10.1 Precision, Recall, and F1-Score per Performance Category (n = 150)

Overall System Performance Summary:

Metric	Value
Overall Accuracy	88.00%
Weighted Average Precision	0.86
Weighted Average Recall	0.84

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Weighted Average F1-Score	0.85
Total Test Samples	150

Table 11.1 Overall System Performance Summary

The method demonstrates a high level of accuracy of 88% with the weighted average F1-score value of 0.85 for all three classes of students. It is worth mentioning that the best results of the classification were achieved in the High Performer group with the F1-score value of 0.89. This result is explained by the distinctive character of features.

Discussion and Result:

First of all, one can conclude that there is a huge practical application of the integration of the cloud environment and data-driven management in classrooms. Indeed, while schools and universities usually have access to an immense amount of background data about learners, this research shows that it is possible to transform it with machine learning algorithms into real educational opportunities. For instance, tracking such factors as logins to LMS and assignments submission can help to predict future performance of the students instead of relying on final exam results. One of the main implications of the research is the ability to intervene timely and provide learners with adequate assistance. It means that when the teacher sees that a particular student demonstrates declining activity, he/she may adjust the strategy and start teaching according to personal characteristics and needs of a learner. Nevertheless, it should be noted that

technology alone cannot solve existing educational problems. At present, there is a significant gap between the availability of information on learners and its application in teaching practices. Indeed, predictive dashboards are useful only if teachers understand how to utilize them. Thus, another important implication of the study lies in providing targeted training courses for teachers. The predictive analytics model created in this study exhibited excellent proficiency in predicting academic success through the use of data from cloud-based learning management systems. The machine learning process yielded predictive accuracies of 88% for predictions made after analyzing the input data, which comprised attendance percentage, quiz performance, assignment completion, and participation in the system. The classification accuracy of our model was assessed through the Random Forest, SVM, and Decision Tree classifiers. The performance of our classification model, in terms of the defined categories of high, medium, and low performers, resulted in a weighted average F1-score of 0.85. Importantly, our model was very accurate in determining which students are considered to be high performers, achieving an F1- score of 0.89 for high-performers. This is indicative of the unique characteristics left by high-performers on the cloud platform.

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Conclusion:

The research provides an effective cloud-based predictive analytics solution for improving education in high educational institutions. Using the integration of machine learning algorithms such as Random Forest, Support Vector Machine, and Decision Tree, along with cloud computing technology and data extracted from LMSs and surveys, the model achieves the classification of students into three performance categories with a total accuracy rate of 88% and a weighted F1-score of 0.85.

Based on the results obtained, one can conclude that cloud-based virtual learning environments combined with management solutions based on collected data may become the driving force behind transforming traditional education into more sophisticated processes. In addition, the results indicate that cloud-based predictive analytics enables teachers to detect problems early, individualize education, and adopt evidence-based decisions in their practice. The validation of primary data by secondary sources is another achievement of this research.

Some of the main contributions from this study are: (1) an advanced set of preprocessing algorithms specifically designed for education data; (2) performance comparison of several algorithms within the realm of student classification problems; (3) a modular and cloud- deployable design; and (4) useful recommendations regarding data-based governance of schools. Importantly, the paper under discussion stresses the pivotal role played by teachers' training and education programs in ensuring that collected data is effectively used within institutions.

On the whole, the suggested approach reveals itself as a very promising basis for constructing intelligent and adaptive educational management systems in developing countries.

Future Work:

While this study provides a robust foundation, several opportunities for future research and improvement of the system can be proposed:

Deep Learning Approaches: In future versions of the system, deep learning algorithms will be implemented, including LSTM and Transformer architectures to capture learning patterns and temporal features based on sequential engagement of students using LMS logs.

Adaptive Real-Time Learning: Adaptation of the model to allow the development of personalized learning paths through real-time analysis of user performance in a cloud environment will be further considered.

Natural Language Processing (NLP): Incorporating NLP approaches to analyze open questions, surveys, forum posts, and comments will help in gaining qualitative insights into the students' learning experience and affective states.

Larger Data Sets and Longitudinal Studies: In future studies, the proposed system will be used to conduct large-scale longitudinal research involving data collected over many years from various institutions in different regions.

Mobile Learning Analytics: Implementation of mobile analytics and application to other IoT enabled learning devices and cloud computing platforms will improve accessibility to the learning environment.

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