

# Learning Analytics in Indian Universities: Developing an Early Warning Framework for Student Success

Richa Vishwakarma<sup>1\*</sup>; Deepika Agrawal<sup>2</sup>

<sup>1</sup>PhD Scholar, Faculty of Arts, Social Science & Humanities, SAM Global University, Raisen (M.P)

<sup>2</sup>Associate Professor, English Language and Literature, Faculty of Arts, Social Science & Humanities, SAM Global University, Raisen (M.P)

Corresponding Author: Richa Vishwakarma<sup>1\*</sup>

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**Abstract:** Learning Management Systems (LMS) collect behavior data that could help universities identify academic risks before they occur, such as during exams or when students withdraw from a course. While the field of learning analytics has been extensively researched worldwide, evidence on the generalization, effectiveness, and transferability of predictive models and corresponding interventions to Indian universities remains limited. This paper examines the potential of LMS-collected data to detect academic risks early, such as disengagement, poor academic results, lack of assignment submission, and dropout risk. The paper conducts a literature review and conceptual synthesis, focusing on educational data mining, behavior prediction, early warning systems, and learning analytics interventions, particularly in Indian higher education. The review concludes that assessment participation, assignment submission behavior, resource use, and online engagement can support prediction. Still, interpretation should depend on course characteristics, data quality and availability, technological capabilities, and measurement timing. Empirical studies in India show that predicting and analyzing educational engagement is possible, yet evidence on the effectiveness of early warning systems at Indian universities remains limited. We introduce an Indian Early Academic Risk Detection Framework (IEARDF) with five interrelated elements: identifying behavioral markers, contextualizing them, predicting risk, human academic intervention, and decision-making. The study distinguishes predictive performance from intervention effectiveness and emphasizes transparency in decision-making, privacy, and equity in student support. The proposed framework provides a basis for empirically validating these concepts.

**Keywords:** Learning Analytics; Indian Higher Education; Learning Management Systems; Academic Risk Prediction; Student Engagement; Early Warning Systems.

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## I. INTRODUCTION

### ➤ Background Context

The proliferation of digital technologies has changed how universities manage teaching and learning and track student progress. Learning Management Systems (LMS) let institutions distribute instructional materials, administer assessments, collect assignments, and provide tools for academic communication. Moreover, such platforms create records of learning activities that can be analyzed to detect changes in engagement and academic challenges. Learning analytics uses educational data to understand and improve the learning process. Long and Siemens [1] highlighted this tool's potential to support educational decision-making by analyzing learning-related information. Later research

expanded learning analytics to include predictions of academic performance, student retention, and early warning systems. Ifenthaler and Yau [2] noted promising applications of learning analytics in supporting student success, while emphasizing the need for stronger evidence of its educational effectiveness. Learning analytics is especially relevant in India, where universities operate under diverse institutional, socioeconomic, and technological circumstances. The National Education Policy 2020 recognizes technology's potential to improve higher education [3]. However, digital infrastructure, instructional practices, and students' access to learning materials can vary, making LMS-generated information difficult to interpret.

A student who rarely accesses online learning materials may become academically disengaged. On the other hand, a student may study offline because of connectivity limitations or take a course in which most instruction takes place in traditional classroom settings. Thus, behavioral data should be contextualized before they can assist educational decision-making. This paper investigates how LMS-produced behavioral data can support early detection of academic risks in Indian universities. The paper develops a framework for early academic risk detection that combines prediction and contextualization.

### ➤ *Problem Statement*

Universities typically identify academic risks through examination results, low attendance rates, incomplete assignments, and teacher observations. Although this information is useful, it may signal academic risks only after students experience major academic setbacks. Learning analytics can identify potentially adverse learning patterns earlier. International research shows that online learning activities and assessment data can predict academic performance. Namoun and Alshanqiti [4] identified several types of predictive techniques and educational variables used in research. However, this research suggests that model performance depends on data characteristics. Indian universities differ in LMS adoption, course delivery, digital infrastructure, and student circumstances, so relationships found in other countries may not hold in Indian universities. Several empirical studies conducted in India have researched educational data mining and digital learning engagement. However, such research does not prove that integrated LMS-based early warning systems can predict academic risk or improve student outcomes across diverse universities. This paper addresses the need for a context-sensitive, empirically testable approach to using LMS-generated behavioral data to detect academic risk early and support appropriate academic intervention.

### ➤ *Research Objectives*

The paper's general goal is to develop a conceptual framework for early academic risk detection using LMS-generated behavioral data in Indian universities. The objectives are as follows:

- To analyze the contribution of learning analytics to academic disengagement, poor performance, and dropout prediction.
- To identify relevant behavioral indicators produced by LMS, including login activity, resource access, attendance, online participation, and assignment submissions.
- To assess the transferability of international predictive models in the context of Indian higher education.
- To develop an integrated framework combining behavioral data, contextualization, risk assessment, and academic intervention.
- To provide recommendations for empirical validation, ethical governance, and institutional implementation.

### ➤ *Research Questions*

The following five research questions are articulated in the paper:

- How can LMS-produced behavioral data contribute to the early detection of academic risks in Indian universities?
- Which behavioral indicators are potentially predictive of academic risks?
- Which institutional and contextual factors influence the transferability of international predictive models?
- How can behavioral prediction and academic intervention be combined in a context-sensitive framework?
- What validation procedures and ethical safeguards should be used before institutional implementation?

## II. RESEARCH METHODOLOGY

The research employs a qualitative conceptual framework based on a literature review. The literature review will analyze peer-reviewed journal articles on learning analytics, educational data mining, predicting student performance, behavioral engagement, and early warnings for students. In addition to international peer-reviewed literature, the review will also cover Indian empirical studies and related policies. The literature review is organized and selective. Scholarly searches using publishers' databases identified sources relevant to the objectives. The focus is on literature relevant to the objectives stated above. The review analyzes articles for behavioral indicators, modeling approaches, intervention measures, institutional barriers, and ethics. The literature review distinguishes between results from predictive studies internationally and those from the Indian context. It also distinguishes between predictive studies and intervention studies. The literature review does not present itself as a systematic or meta-review. The authors collected no student data and did not create a predictive model.

## III. LITERATURE REVIEW

### ➤ *Context of the Evolution of Learning Analytics*

Learning analytics developed alongside the growing popularity of digital learning environments and new approaches to analyzing educational data. In the early stages, institutions monitored learning through exam results, attendance figures, and administrative data. Later, LMS platforms let researchers examine learning activity across entire courses. Long and Siemens [1] noted the importance of collecting learning data in order to enrich the educational knowledge base and support decision-making. Over time, the field expanded to include predictive models, student dashboards, and early warning systems. Ifenthaler and Yau [2] reviewed learning analytics applications designed to promote student success and discussed possibilities for academic monitoring and intervention. Akçapınar et al. [5] explored using online interaction data to identify students who might struggle before the end of the course.

Recently, researchers have placed greater emphasis on the relationship between analytical findings and educational interventions. In their systematic review of learning analytics interventions in LMS environments, Pan et al. [6] found a

growing tendency to use analytical results in educational processes. Drugova et al. [7] analyzed learning analytics applications focused on improving learning design. These authors concluded that educational data can be used not only to predict student outcomes but also to analyze and optimize instructional design. However, to use learning analytics successfully in Indian universities, one should consider institutional particularities and the purposes of data collection.

#### ➤ *LMS Behavioral Indicators*

LMS behavioral records contain information about student interactions with the digital learning environment. Examples of such behavioral indicators include log-ins, accessing of resources, submitting of assignments, participating in assessments, and online interaction. Although login frequency may serve as a proxy for regular digital activity, it does not, on its own, indicate meaningful learning. Some students might access a system without learning, while others might learn offline. Accessing resources can provide additional information about participation in learning activities; however, that information may depend on how instruction was designed, because frequent access to resources can be seen as either engagement or a sign of difficulty understanding the material. Data on submitted assignments and submission time will be more reliable for participation in formally assessed activities. Namoun and Alshanqiti [4] noted that assessment information and online learning activity were two variables used in research to predict student performance. According to Kuzilek et al. [8], the Open University Learning Analytics Dataset included assessment information and interactions within a virtual learning environment. The dataset shows analytical potential for long-term records; however, conclusions drawn from it cannot be generalized to Indian universities. Attendance data can supplement LMS records when available and reliable. However, LMSs do not capture attendance at physical classes, so this data may require integration with other institutional systems. The timing of measurements is the next issue to consider. Both attendance and assignment submission can predict future academic performance, but they can also be outcomes of interest. Missed assignments in the first weeks of the semester can predict whether students will have future non-submissions. Using any information collected after the prediction point is considered data leakage and leads to better-than-real performance.

#### ➤ *Predictive Models and Early Warning Systems*

Predictive learning analytics uses statistical and computational methods to estimate a student's future academic outcomes. Widely used methods include support vector machines, decision trees, logistic regression, random forests, and artificial neural networks. Namoun and Alshanqiti [4] noted significant variation in predictive techniques and input variables. A technique's suitability depends on institutional data, outcome definitions, and the purpose of the educational intervention. Akçapınar et al. [5] showed the relevance of analysis of past online interactions for academic risk detection. Such approaches help because early predictions create opportunities for academic intervention. Jayaprakash et al. [9] evaluated an early-alert

initiative to identify academically at-risk students and enable institutional intervention. This study further illustrates the link between predictions and practical student support.

However, predictive accuracy does not prove a technique's educational effectiveness. Larrabee Sønderlund et al. [10] pointed out the limitations in the evidence concerning learning analytics interventions. Subsequent research has improved the evidence base. In a meta-analysis of empirical studies, Liu et al. [11] found that learning analytics interventions improved learning outcomes, but effects varied by intervention and outcome category. This shows that learning analytics can support educational improvement, but its effectiveness is not uniform. Evaluating a model's performance requires appropriate statistics; accuracy can be misleading when estimating rare academic risk outcomes. Precision, recall, calibration, and subgroup performance provide additional insight into a model's reliability. Therefore, an effective early warning system should balance predictive performance, interpretability, intervention timing, and educational consequences of incorrect predictions.

#### ➤ *Indian Higher Education Context*

Indian universities operate in diverse institutional and technological environments. The National Education Policy 2020 advocates digital transformation [3], but LMS adoption and integration can vary widely among institutions. Differences in course delivery, digital infrastructure, and student access to devices can affect learning activity. In a predominantly classroom-based course, LMS records would provide a partial record of the students' learning activities. Indian research provides relevant evidence. Dabhade et al. [12] explored how educational data mining techniques could predict students' academic performance at a technical institution in India. The study shows the feasibility of using machine learning on Indian academic data, but it does not demonstrate the effectiveness of an LMS-integrated intervention system. Majumdar et al. [13] examined digital reading behavior in a humanities course at an Indian university. The analysis revealed distinct reading engagement profiles, demonstrating the value of analyzing learning interactions in the Indian educational context. However, the activity-specific design and limited sample size do not establish predictive validity for dropout and institutional retention. This distinction matters because research on predicting academic performance and digital engagement in India exists, but this study's findings cannot serve as evidence for the effectiveness of a universal early warning framework across Indian universities. Márquez et al. [14] identified institutional and organizational factors affecting learning analytics adoption in higher education. This finding highlights the importance of evaluating institutional readiness alongside modeling.

#### ➤ *Research Gaps*

The literature above reveals several unresolved issues.

The predictive models require more contextual validation. Findings from international studies cannot automatically transfer to Indian universities because of

differences in instructional design, digital infrastructure, and student demographics.

Interpretation of the LMS-generated behavioral data requires caution. Low digital participation can indicate disengagement, but it can also reflect offline study, connectivity issues, or specific instructional practices.

Predictive research requires linkage to the evidence on intervention effectiveness. Recent research shows positive impacts of learning analytics interventions [11], but the extent of these impacts in Indian universities remains uncertain.

Ethical issues should be considered in more detail. Slade and Prinsloo [15] highlighted ethical concerns about student privacy, surveillance, and institutional responsibilities, which become especially relevant when predictions shape academic intervention decisions.

García-García et al. [16], in their recent meta-review, identified methodological limitations and a lack of attention to educational context in learning analytics research.

Thus, this paper addresses a key gap in the literature: the need for a context-sensitive framework that links behavioral predictions, contextualization, human-reviewed academic intervention, and empirical validation in Indian higher education.

#### ➤ *Key Findings from Literature Review*

##### • *Predictive Value of Behavioral Indicators*

The reviewed literature shows that LMS-generated behavioral data can identify academically at-risk students. However, their predictive value depends on how indicators are selected, combined, and interpreted. Participation in assessments and assignment submission patterns can provide information about participation in formally evaluated academic activities. Frequent delays, missed assignments, and lower assessment participation can indicate emerging academic risks. Login frequency and resource access provide complementary information, but they are less informative indicators of academic achievement [4,8].

Changes in behavioral indicators over time can be more informative than individual indicator values. However, empirical evidence is needed to confirm the importance of changes, and their significance cannot be assumed to be the same across courses or institutions. Indian studies demonstrate the feasibility of educational prediction and digital engagement analysis in specific institutional contexts [12,13]. However, the findings do not prove that a universal set of LMS indicators reliably predicts academic risk in Indian universities. Moreover, the literature shows that predictive reliability and intervention effectiveness are separate concerns. While learning analytics interventions can produce educational benefits [11], institutions should evaluate whether they can achieve these benefits in their specific educational context. These considerations show the need to develop a framework that integrates behavioral

indicators, contextualization, appropriate timing of predictions, and evaluated academic interventions.

##### • *Indian Early Academic Risk Detection Framework*

This paper proposes the Indian Early Academic Risk Detection Framework (IEARDF) as a conceptual framework for early detection and resolution of academic risks in Indian universities. IEARDF includes five interrelated aspects.

##### • *Behavioral Data Identification*

The first component includes identifying measurable indicators of engagement, such as LMS login activity, access to learning resources, assessments, assignment submission patterns, online discussion, and attendance, where institutional records are available. Each indicator must be precisely defined; for instance, define assignment completion as the ratio of completed assignments to planned assignments up to a certain point in time. Changes in engagement may be explored over a period of consecutive academic weeks. Universities must distinguish between data available at the prediction date and outcomes to avoid data leakage and realistically evaluate the effectiveness of early warnings.

##### • *Contextual Data Interpretation*

The second component concerns institutional contexts that may affect behavioral indicators. Context, including course design, teaching methods, digital infrastructure, and access to learning resources, may shape students' LMS activity. Student login activity may mean something different in fully online and traditional courses. Therefore, the proposed framework suggests that universities first explore context and then interpret behaviors as indicators of academic risk, paying particular attention to Indian institutions where digital learning practices may differ. In addition, researchers need to examine the causes of missing records, whether low student engagement or weak institutional data-collection processes.

##### • *Predictive Risk Assessment*

The third component relates to estimation of the probability of specific academic outcomes. Potential outcomes may include disengagement, poor assessment performance, repeated assignment non-completion, and course withdrawal. Each potential outcome requires its own definition and prediction horizon. Universities may begin with relatively straightforward statistical analysis, such as logistic regression and decision trees, before assessing more sophisticated machine learning approaches. Model evaluation shall include precision, recall, calibration, and appropriate subgroup analyses. Thresholds for risks shall be empirically defined rather than arbitrarily assumed. Predictions need to be uncertain and intelligible to academics. Academic Intervention and Student Support.

##### • *Connecting Risk Identification with Academic Institutions*

The fourth component links risk classification with educational support for students. Potentially at-risk students may need mentoring, academic counseling, tutoring, help with assignment planning, or access to learning resources. Jayaprakash et al. [9] demonstrate the practical relevance of connecting academic risk identification with institutional

interventions. Bodily and Verbert [17] examined student-facing learning analytics dashboards and recommendation systems, showing how analytical information could support students. In IEARDF, predictive classifications should prompt support rather than punishment. Academics need to review information about potentially at-risk students and consult with them before choosing the proper actions.

- *Institutional Validation and Continuous Evaluation*

The fifth component includes evaluation of the reliability of predictions and educational effectiveness. Universities need to validate models with real student-level records and defined outcomes. Separate training and testing periods are needed to estimate whether predictions remain reliable for subsequent student cohorts. Ideally, external validation should assess models' predictive power across institutions and disciplines. Intervention evaluation needs to be conducted separately. Institutions need to determine whether students receive appropriate assistance and whether it increases engagement, performance, or retention. Validation study results should guide further improvements to indicators, predictive models, intervention procedures, and data governance practices. The IEARDF cannot be reduced to a classification model since it is an institutional decision-support framework that incorporates behavioral evidence, contextual interpretation, human judgment, and measurable outcomes. IEARDF's main contribution is incorporating these elements into the Indian higher education research agenda, which requires empirical validation.

#### IV. LIMITATIONS AND VALIDATION REQUIREMENTS

The proposed framework was not validated using original student-level data; therefore, its predictive reliability and educational effectiveness remain unproven. The first limitation concerns the completeness of LMS records because institutions may differ in platform adoption, data retention, and integration with assessment or attendance systems. Missing records may reflect institutional practices rather than a lack of student engagement. Behavioral interpretation is another challenge since offline learning, connectivity issues, and differences in instructional design may affect activities recorded by analytics systems. This means predictive models may produce misleading classifications if they do not consider relevant contexts. Ethical aspects are also vital. Drachsler and Greller [18] suggested the DELICATE checklist to promote trustworthy learning analytics by ensuring proper handling of educational data. Universities need to establish appropriate protections for privacy, transparency, access control, and human supervision.

#### V. RECOMMENDATIONS

Accordingly, the proposed strategy for deploying learning analytics in India includes three phases: initial focus on well-defined educational goals and sound data practices, development and testing of predictive models, and implementation of academic interventions supported by predictive information.

##### ➤ *Improvement of Data Infrastructure of Learning Management Systems (LMS)*

The universities should develop procedures for collecting and maintaining behavioral data. Clear definitions of logins, resource access, assignment submission, assessments, and attendance are necessary to improve data comparability. Data audits should identify missing records, timestamp issues, duplicates, and differences in LMS usage at the course level. In addition, it is necessary to document learning activities conducted offline. As Drugova et al. [7] show, considering the connection between learning analytics and instructional design is significant; therefore, the data should reflect the learning activities expected for each course, rather than general platform usage.

##### ➤ *Development of Context-Specific Predictive Models*

Build predictive models on real institutional records and well-defined academic outcomes. First, studies should compare the interpretability of statistical approaches and selected machine learning approaches. Evaluation of predictive models should include predictive performance, transparency, institutional capacity, and the consequences of misclassification. Several models may be needed, since predicting non-completion of assignments differs from predicting dropouts. Each model should have an informational base prior to the period of the outcome. The predictive validity could differ by discipline, type of course and demographic groups of students; therefore, the models should be periodically reviewed.

##### ➤ *Development of Academic Intervention Mechanisms*

Universities should implement an early warning system within the existing academic support structure. The universities should develop procedures for reviewing alerts, communicating with students, identifying problems, and providing appropriate assistance. Mentors, advisors, and other student support services could perform this kind of intervention. Interventions should be supportive, not punitive. In addition, classification results should not be the sole basis for decision-making. As Liu et al. [11] note, some evidence suggests that learning analytics interventions can positively affect learning outcomes; however, effectiveness varies. Therefore, Indian universities should evaluate intervention results rather than assuming that predictive information automatically improves student outcomes.

##### ➤ *Implementation of Ethical Data Governance*

The universities should develop transparent policies for collection, processing, access, storage and usage of education data. Students should be informed about the purposes of learning analytics and possible consequences of risk classifications. Institutions should identify valid legal grounds for processing personal data and apply appropriate technical measures to comply with India's data protection requirements. Data governance should be based on the key aspects of ethical data governance formulated by Slade and Prinsloo [15] and the practical recommendations provided by Drachsler and Greller [18]. Periodic assessments of model fairness should reveal whether predictive mistakes significantly affect specific student groups. The

implementation process should include human oversight and the possibility of appeals in cases of misclassification.

#### ➤ *Conducting of Pilot Studies in the Universities*

The proposed framework should first be evaluated through limited pilot studies at universities that represent various institutional and technological contexts. Early studies should assess whether behavioral data collected at the beginning of a semester can predict future academic problems. Evaluating predictive models should include data from a subsequent period that was not available when predictions were made. Further studies should evaluate the effectiveness of academic interventions using appropriate comparative or longitudinal research designs. When possible, a controlled experiment will provide stronger evidence of intervention effectiveness. According to Hellings and Haelermans [19], the experimental evaluation is important when investigating how learning analytics information influences the behavior of students. External validation of models in different institutions will show whether predictive relationships hold outside the development context.

#### ➤ *Increasing Faculty and Institutional Capacity*

Deploying learning analytics requires preparedness among academic staff and cooperation within institutions. Academic staff should be trained to interpret predictive information and respond appropriately to student problems. Technical staff should cooperate with academic departments and student support services to integrate educational process requirements into the analytical system. Márquez et al. [14] identify factors that determine the adoption of learning analytics, including governance, institutional readiness, and stakeholder involvement. Periodic reviews of model performance, intervention outcomes, and student feedback are necessary to avoid reducing learning analytics to a technological solution. Therefore, the proposed implementation strategy is incremental. Institutions should establish strong data practices, conduct limited predictive testing, evaluate academic interventions, and proceed with implementation only after confirming its reliability, fairness, and educational value.

## VI. CONCLUSION

This research examines the potential of using LMS-generated behavioral data to detect academic risk factors among students in Indian universities. From the literature review, we conclude that such factors as online activities, participation in tests, and assignment submission may play a role in academic risk prediction; however, the use of such data is conditional to a number of factors like instructional design, data quality, time, and context of predictions. Available empirical evidence suggests that educational data mining and digital engagement analysis are applicable to higher education in India. However, it cannot be concluded that LMS-based early warning systems are generally effective across Indian universities. This research is significant because it highlights the need for a more robust Indian Early Academic Risk Detection Framework. By incorporating five components- identification of behavioral data, contextual interpretation, academic risk prediction, intervention, and

institutional validation- the framework provides a basis for further empirical studies. It is important to reiterate that predictive accuracy and the effectiveness of educational measures are different. Identifying potentially risky students does not always lead to positive educational outcomes. Achieving them requires proper institutional context, responsible interpretation, and evaluation of intervention effects.

Because the proposed framework has not yet been empirically tested, we cannot yet confirm its predictive accuracy and effectiveness. Future research should empirically test the framework's performance on data from Indian universities, compare predictive models, and examine the potential effects of timely interventions. Learning analytics offer many promising opportunities to improve support for higher education students in India. To realize them effectively, more than technological capabilities alone is needed. Researchers should consider prediction validity, ethical implications, human interpretation, and educational benefits.

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