CHAPTER 5

EARLY WARNİNG SYSTEMS FOR IDENTİFYİNG AT-RİSK LEARNERS İN INDİA: A QUALİTATİVE STUDY

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Abstract

The issue of studying at risk learners who may fail academically, become disengaged, drop out, or delayed development is of a vital concern in the Indian education system. Even with the enrolment advancement, a high number of students are still exposed to structural, academic, socio-economic, and psychological barriers that influence retention and educational achievement. Here, Early Warning Systems (EWS) have become a pioneering international set of strategies that can be used to proactively recognize vulnerable students and learners prior to the irreversible consequences of educational failure. This paper discusses the idea, importance, relevance and issues of Early Warning Systems in detecting at-risk learners in India. The research methodology is the qualitative review-based approach and relies on the official policy reports, books, and journals. The paper tells about recent school dropout in India, the applicability of EWS according to the National Education Policy (NEP) 2020, the opportunities of learning analytics, attendance data, academic records, and behavioural indicators to create an Indian model of learner support. The results indicate that India is in dire need of institutionalized early identification systems, particularly in school and higher education environments that are characterized by digital inequality, first-generation students, and diverse educational preparedness. The paper concludes that EWS can be a significant educational facilitating tool in India provided it is adopted ethically, contextually and with robust human intervention systems and not as merely technological surveillance tools.

Keywords: *Early Warning Systems, At-Risk Learners, India, Dropout, Learning Analytics, Student Retention, NEP 2020, Educational Data Mining.*

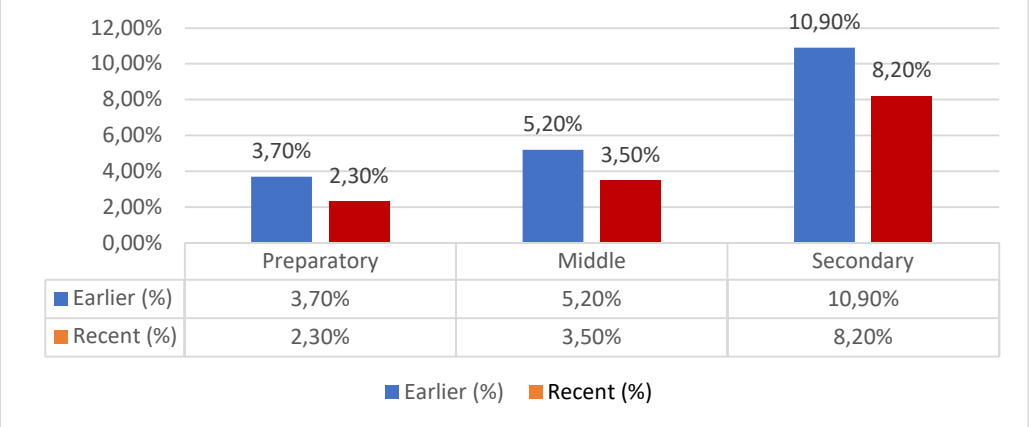
Introduction

India is home to one of the largest and most complex education systems in the world, encompassing millions of learners across school, college, and university levels. Over the past two

decades, substantial progress has been made in expanding access to education through policy reforms, infrastructural development, and increased public investment in universal education [10–12]. However, access alone does not ensure meaningful participation, academic progression, or successful completion. A significant proportion of learners continue to face challenges such as poor academic performance, disengagement, irregular attendance, examination failure, and eventual dropout. This persistent gap between enrolment and educational success remains one of the most pressing concerns within the Indian education system [16].

Recent national data highlights both progress and ongoing challenges. According to the Economic Survey 2024–25, dropout rates stand at 1.9% at the primary level, 5.2% at the upper primary level, and 14.1% at the secondary level, indicating a sharp increase as students advance through the system [11]. Similarly, UDISE+ data for 2024–25 reports a decline in dropout rates—from 3.7% to 2.3% at the preparatory level, 5.2% to 3.5% at the middle level, and 10.9% to 8.2% at the secondary level—suggesting improvement, yet continued vulnerability at higher levels of schooling [12]. These figures reveal a critical pattern: while access has improved, retention and engagement remain fragile, particularly during transitional stages marked by academic pressure, socio-economic constraints, and reduced motivation.

Graph -1 Represent Comparative Analysis of Student Dropout Rates by Educational Stage



Source: Economic Survey 2024–25

In this context, the need for proactive and data-driven interventions becomes evident. Early Warning Systems (EWS) have emerged as a strategic response to identify and support at-risk learners before they disengage or drop out. EWS are structured, evidence-based frameworks that utilize indicators such as attendance records, academic performance, behavioural patterns, and

socio-economic background to detect early signs of risk [5]. Unlike traditional reactive approaches, these systems enable preventive interventions through timely identification and targeted support mechanisms [6,14].

The application of learning analytics and educational data mining has significantly strengthened the effectiveness of EWS. Studies demonstrate that predictive models using machine learning algorithms can accurately identify students at risk by analysing patterns in digital engagement, assessment performance, and participation [8,13,15]. Research in online and blended learning environments further confirms that EWS can enhance retention rates by enabling personalized interventions and continuous monitoring [6,7]. Moreover, systematic reviews highlight that learning analytics plays a crucial role in reducing dropout rates and improving academic outcomes in higher education [4,17].

The relevance of EWS in India has become even more pronounced in the post-pandemic context. The COVID-19 crisis exposed deep structural inequalities, including the digital divide, learning loss, disrupted routines, and increased psychological stress among students [16]. These challenges have intensified the need for robust monitoring systems that can track learner progress and provide timely academic and emotional support. The National Education Policy (NEP) 2020 further reinforces this need by emphasizing equity, inclusion, flexibility, and reduced dropout rates, thereby creating a strong policy foundation for the integration of EWS in educational institutions [10].

Globally, early warning frameworks have been successfully implemented across various domains, including finance, disaster management, and environmental risk assessment, demonstrating their adaptability and effectiveness in predictive modelling [1,2,3]. Their application in education represents a natural extension of these approaches, where data-driven insights can inform decision-making and improve institutional responsiveness [18]. In the Indian context, integrating EWS within the education system can significantly enhance learner retention, promote inclusive education, and align with national development goals.

Thus, the adoption of Early Warning Systems represents a critical shift from reactive to preventive educational practices. By leveraging data, technology, and policy support, EWS can play a transformative role in addressing the enrolment–achievement gap and ensuring that access to education translates into meaningful learning outcomes and long-term success [9].

Review of Related Literature

The concept of early identification of at-risk learners before formal academic failure had received considerable attention within the domains of learning analytics, educational data mining, and student retention research. International scholarship consistently demonstrated that students exhibited measurable early warning indicators—such as absenteeism, low digital engagement, poor assessment performance, delayed submissions, and reduced participation—well before actual failure or dropout occurred [13,14,17]. These observable patterns provided a strong empirical foundation for the development of Early Warning Systems (EWS) aimed at timely intervention and learner support.

A seminal study by Akçapınar et al. had highlighted the role of learning analytics in identifying at-risk students through digital traces of learner behaviour in online environments [5]. Their findings suggested that analysing real-time engagement data enabled institutions to detect potential academic risk during the learning process rather than after final assessments. Importantly, the study emphasized that predictive accuracy improved significantly when multiple indicators—academic, behavioural, and interactional—were combined instead of being used in isolation [5]. This multidimensional approach enhanced the reliability of early identification models and strengthened risk detection frameworks.

Similarly, Bañeres et al. had developed an EWS model in online higher education and demonstrated that predictive analytics could effectively identify students at risk of disengagement or academic failure [6]. However, they argued that prediction alone was insufficient and that the true pedagogical value of EWS lay in enabling timely, personalized, and context-sensitive interventions. This perspective reinforced the idea that EWS functioned not merely as diagnostic tools but as mechanisms for proactive academic support and student retention improvement [6].

Further strengthening this argument, de Oliveira et al. conducted a systematic review and concluded that learning analytics contributed significantly to dropout prevention when institutions actively used learner data to support student persistence rather than simply record outcomes [4]. Likewise, Queiroga et al. found that early identification allowed institutions to design targeted interventions, thereby improving student retention and academic continuity [14]. These studies collectively underlined the importance of integrating academic performance with behavioural and participation-based indicators to enhance the effectiveness of EWS frameworks.

Recent advancements in machine learning further expanded the scope of early detection models. Techniques such as decision trees, logistic regression, support vector machines, random forests, and neural networks had been increasingly applied to predict student risk profiles [8,15].

Research indicated that combining static variables (such as socio-economic background) with dynamic variables (such as weekly engagement patterns) significantly improved predictive accuracy, particularly when analysed longitudinally rather than at a single point in time [8]. This dynamic modelling approach enabled continuous monitoring and adaptive intervention strategies within educational systems.

In the Indian context, large-scale empirical research on EWS remained limited; however, existing policy documents and educational studies strongly indicated the need for such systems. Key challenges such as irregular attendance, foundational learning gaps, socio-economic disparities, and transitional vulnerabilities between educational stages were consistently reported [11,12,16]. Evidence suggested that while enrolment rates appeared high, actual classroom engagement and participation varied significantly, making attendance and engagement critical indicators of student risk [16].

The policy environment in India further supported the conceptual relevance of EWS. The National Education Policy (NEP) 2020 emphasized equity, inclusion, flexible learning pathways, and reduced dropout rates, all of which aligned closely with early identification and intervention frameworks [10]. Although EWS had not yet been systematically institutionalized across Indian education systems, its theoretical and policy foundations had become increasingly evident.

Objectives of the Study

The present paper is guided by the following objectives:

1. To find out the concept and significance of Early Warning Systems for identifying at-risk learners.
2. To study the relevance of Early Warning Systems in the Indian educational context.
3. To find out the major indicators that can be used to detect at-risk learners in India.
4. To explore the role of educational data, learning analytics, and institutional intervention in building an Early Warning System.
5. To find out the educational implications, opportunities, and challenges of implementing EWS in India.

Methodology

The current research uses a qualitative research approach as a review. It is conceptual, interpretive in nature and it does not contain collection of primary field data. Rather the paper relies on secondary data and academic analysis.

Nature of the Study

This article is a qualitative journal-type review paper that aims at the conceptual, policy and practical relevance of the Early Warning Systems to identify at risk learners in India.

Sources of Data

The present study is grounded in a comprehensive and systematic review of diverse categories of academic and policy-oriented sources, ensuring both theoretical depth and empirical relevance. A significant portion of the literature has been drawn from peer-reviewed journal articles available through academic databases such as Google Scholar. These studies provide rigorous, evidence-based insights into learning analytics, educational data mining, student retention, and **Early Warning Systems (EWS).** Foundational works in this domain highlight the role of predictive analytics, behavioural indicators, and digital engagement in identifying at-risk learners and improving educational outcomes [5,13,17]. Such peer-reviewed contributions form the backbone of the analytical framework employed in this research.

In addition to journal articles, scholarly papers accessed through reputed journal have been extensively utilized to capture emerging trends and recent developments in the field. These sources include contemporary studies on machine learning applications in education, predictive modelling of student performance, and the integration of artificial intelligence in early detection systems [8,15]. Publications often provide access to preprints and ongoing research, thereby offering timely and relevant perspectives that complement traditional peer-reviewed literature.

Official reports and publications by the Ministry of Education, Government of India, constitute another critical category of sources. Documents such as the National Education Policy (NEP) 2020 and the Economic Survey 2024–25 provide authoritative insights into the policy landscape, educational priorities, and systemic challenges within the Indian context [10,11]. These reports are essential for understanding the structural dimensions of education, including access, equity, inclusion, and dropout trends, which directly inform the need for Early Warning Systems.

National education databases, particularly UDISE+ (Unified District Information System for Education) and AISHE (All India Survey on Higher Education), serve as vital sources of quantitative data. These databases offer large-scale, longitudinal data on enrolment, attendance, dropout rates, and institutional performance across different levels of education [12]. The use of such datasets enhances the empirical grounding of the study by providing measurable indicators of learner vulnerability and educational disparities.

Furthermore, international reports and studies focusing on student retention, dropout prevention, and learning analytics have been incorporated to provide a global perspective. Reports by organizations such as UNESCO and UNICEF, along with comparative studies in educational technology, highlight best practices and conceptual frameworks for implementing EWS in diverse educational settings [16]. These global insights help situate the Indian experience within a broader international discourse on sustainable and inclusive education.

Policy documents, particularly the National Education Policy (NEP) 2020, play a central role in shaping the conceptual foundation of this study. NEP 2020 emphasizes learner-centric approaches, flexible progression pathways, reduced dropout rates, and the integration of technology in education, all of which align closely with the principles of Early Warning Systems [10]. The policy's focus on equity, inclusion, and holistic development further reinforces the relevance of EWS as a tool for achieving sustainable educational outcomes.

The integration of peer-reviewed research, scholarly publications, official reports, national databases, and international policy frameworks ensures a multidimensional approach to the study. This diverse source base not only strengthens the validity and reliability of the research but also enables a comprehensive understanding of the need, scope, and implementation of Early Warning Systems in the Indian educational context [4,6,14].

Method of Analysis

The present study employs a qualitative synthesis approach grounded in thematic analysis to examine the collected literature on Early Warning Systems (EWS) and at-risk learners. This methodological choice is particularly suitable for an emerging research area like EWS in India, where conceptual clarity, contextual interpretation, and policy relevance are more critical than purely statistical generalization [8,16]. The gathered information has been systematically analysed across key thematic categories to provide a comprehensive understanding of the subject.

The first theme focuses on the theoretical understanding of at-risk learners. Existing research in learning analytics and educational data mining suggests that at-risk status is not an abrupt condition but a gradual process characterized by observable indicators such as declining academic performance, absenteeism, low engagement, and socio-economic vulnerability [13,15]. Foundational models of learning analytics further emphasize the importance of tracking learner behaviour and interaction patterns to understand risk trajectories over time [7]. These theoretical insights establish the basis for early identification frameworks.

The second theme explores the role of EWS in learner support. Studies demonstrate that EWS function as structured, data-driven systems designed to identify students at risk and enable timely intervention [5,6]. Importantly, the effectiveness of these systems depends on the integration of predictive analytics with meaningful pedagogical responses, such as mentoring, academic support, and personalized feedback [6,17]. Research also highlights that early identification combined with intervention significantly improves retention and academic outcomes [14].

The third thematic category addresses indicators of educational risk. Empirical evidence shows that combining multiple indicators—academic performance, attendance, participation, and digital engagement—enhances predictive accuracy [5,15]. Advanced machine learning models, including ensemble learning techniques, have further improved the capacity to detect at-risk students by integrating both static and dynamic variables [9,20]. These approaches enable continuous monitoring and adaptive intervention, making EWS more effective and responsive.

The fourth theme examines dropout trends and participation patterns in India. National reports such as the Economic Survey 2024–25 and UDISE+ data highlight persistent challenges in student retention, particularly at higher levels of schooling [11,12]. Despite improvements in enrolment, disparities in participation and completion remain significant due to socio-economic inequalities and learning gaps [16]. These findings underscore the urgent need for systematic mechanisms to identify and support vulnerable learners.

The fifth theme considers the implementation possibilities of EWS in Indian institutions. Although large-scale institutional adoption is still limited, policy frameworks such as the National Education Policy (NEP) 2020 emphasize equity, inclusion, and technology-enabled learning, aligning closely with the principles of EWS [10]. Additionally, studies from other domains, such as disaster management and environmental risk prediction, demonstrate the adaptability and

effectiveness of early warning frameworks in complex systems [1,2,19]. These insights suggest strong potential for the integration of EWS within Indian education.

The qualitative synthesis approach enables a multidimensional analysis by integrating theoretical, empirical, and policy perspectives. Given the developmental stage of EWS in India, this method provides a robust framework for understanding its relevance, challenges, and future potential beyond mere statistical description [4,8,16].

Understanding At-Risk Learners in India

The concept of the at-risk learner has gained increasing attention in contemporary educational research, particularly within the domains of learning analytics, student retention, and educational equity. An at-risk learner is not necessarily one who has already failed, but one who shows early signs of vulnerability that may lead to academic underachievement, disengagement, or eventual dropout if timely intervention is not provided [5,8,14]. This conceptual shift from outcome-based identification to process-based monitoring is crucial for developing responsive and preventive educational systems.

In the Indian context, the condition of being "at risk" is deeply embedded in structural and socio-economic inequalities. Unlike purely performance-based interpretations, research suggests that educational vulnerability often arises from a combination of contextual and behavioural factors rather than individual incapacity [10,11,12]. Poverty and financial stress, for instance, significantly affect students' ability to access resources, maintain continuity in education, and remain motivated [16,17]. Similarly, weak foundational learning—particularly in literacy and numeracy—creates long-term academic difficulties that accumulate over time, especially during transitions from primary to secondary education [11,16].

First-generation learners and students from rural or remote areas face additional barriers due to limited academic support at home and inadequate institutional infrastructure [12,16]. These challenges are further intensified by limited digital access, which became highly visible during and after the COVID-19 pandemic, highlighting disparities in participation in online learning environments [17,18]. Language barriers also play a critical role, as students studying in non-native or unfamiliar mediums often struggle to engage meaningfully with curriculum content [10]. Gendered expectations, commuting burdens, and family caregiving responsibilities disproportionately affect certain groups, particularly girls, influencing attendance, participation, and continuity in education [16,17].

Beyond structural factors, psychological and emotional dimensions such as stress, anxiety, and lack of self-efficacy contribute significantly to learner vulnerability. These aspects are often invisible in formal records but strongly influence engagement and performance [8,18]. Research in learning analytics demonstrates that early indicators such as absenteeism, low participation in digital platforms, delayed assignment submission, and reduced interaction with teachers are strong predictors of future academic risk [5,6,15]. Romero et al. emphasized that patterns of online engagement can effectively predict student performance long before final assessments occur [15].

Importantly, the Indian educational landscape presents a unique challenge where risk is often "silent." A student may remain officially enrolled but gradually disengage from the learning process through irregular attendance, minimal participation, and declining motivation [11,12]. Such students may not immediately appear in dropout statistics, yet they represent a significant portion of the vulnerable population. Therefore, relying solely on examination outcomes provides an incomplete understanding of educational risk.

This underscores the importance of Early Warning Systems (EWS) in education. EWS frameworks emphasize continuous monitoring of multiple indicators—academic, behavioural, and socio-economic—to identify emerging vulnerabilities rather than reacting to failure after it occurs [5,6,13]. Studies have shown that combining multiple indicators improves predictive accuracy and allows institutions to design timely and targeted interventions [5,9]. Moreover, machine learning approaches further enhance the ability to track dynamic patterns of student engagement over time, making early identification more precise and actionable [9,20].

Identifying at-risk learners in India requires a multidimensional and context-sensitive approach that goes beyond traditional examination metrics. Early Warning Systems offer a transformative framework by focusing on patterns of vulnerability, enabling institutions to shift from reactive to preventive educational practices. Such systems are essential for promoting equity, improving retention, and ensuring that all learners are provided with meaningful opportunities to succeed [5,16,17].

Why India Needs Early Warning Systems

The need for Early Warning Systems (EWS) in India emerges from multiple structural, pedagogical, and policy-related realities that continue to shape the educational landscape. Despite significant expansion in access to education, challenges related to retention, engagement, and progression remain persistent across different levels of schooling and higher education [10,11,16]. EWS provides a systematic and data-driven approach to identifying learners at risk before academic failure or dropout occurs, thereby enabling timely intervention and support.

One of the most critical concerns is the persistence of dropout and progression loss. Although India has made notable progress in reducing dropout rates over the years, recent national statistics indicate that the risk of dropout increases significantly at higher levels of education, particularly during the transition from upper primary to secondary stages [11,12]. This trend reflects the growing academic pressure, socio-economic constraints, and disengagement that learners experience as they move through the system. Learning analytics research suggests that such risks can be anticipated through early behavioural and academic indicators, allowing institutions to intervene before disengagement becomes irreversible [5,14,15].

Another major concern is the fragility of attendance and engagement. In many Indian educational settings, enrolment figures do not accurately reflect actual participation. Studies have shown that even in contexts with near-universal enrolment, regular attendance and active engagement remain inconsistent [16]. Indicators such as absenteeism, reduced classroom interaction, and low participation in digital learning environments are strong predictors of educational vulnerability [5,6]. EWS frameworks emphasize the importance of tracking these behavioural patterns over time, as they often precede academic decline and eventual dropout [13,15].

The post-pandemic educational scenario has further intensified the need for EWS. The COVID-19 pandemic exposed and widened existing inequalities in digital access, learning continuity, and student support systems. Many learners returned to formal education with disrupted study habits, reduced motivation, and weakened academic confidence [16,17]. Research on digital learning environments highlights that gaps in engagement and participation can persist even after students re-enter classrooms, making it essential to identify and support those who struggle to reintegrate [18,20]. EWS can play a crucial role in detecting such patterns of disengagement and facilitating targeted remedial measures.

The relevance of EWS is also closely aligned with the vision of the National Education Policy (NEP) 2020. The policy emphasizes learner-centric education, inclusivity, flexibility in curricular progression, and reduction of dropout rates [10]. Achieving these goals requires robust mechanisms for continuous monitoring and early identification of learner vulnerability. EWS supports this policy direction by providing institutions with tools to track academic performance, attendance, and behavioural indicators in a systematic manner, thereby enabling proactive educational planning and intervention [11,12].

Furthermore, EWS contributes to strengthening institutional accountability. Traditionally, student failure in India has often been attributed to individual shortcomings rather than systemic issues. However, contemporary research in educational data mining and learning analytics emphasizes that institutions share responsibility for identifying and addressing learner challenges [13,18]. When early warning signs such as declining performance or absenteeism are ignored, the system itself contributes to student exclusion. EWS shifts the focus from reactive assessment to proactive support, encouraging institutions to take responsibility for student success and retention [6,9].

The implementation of Early Warning Systems in India is not merely a technological innovation but an educational necessity. By addressing issues of dropout, engagement, post-pandemic disruption, policy alignment, and institutional accountability, EWS offers a comprehensive framework for improving educational outcomes. It enables a transition from a reactive to a preventive model of education, ensuring that learners receive timely support and opportunities for sustained academic success [5,16,17].

Core Components of an Early Warning System

A functional Early Warning System usually includes four interconnected components:

Data Collection

Recent School Dropout Rates in India (Official UDISE+/Government Sources)

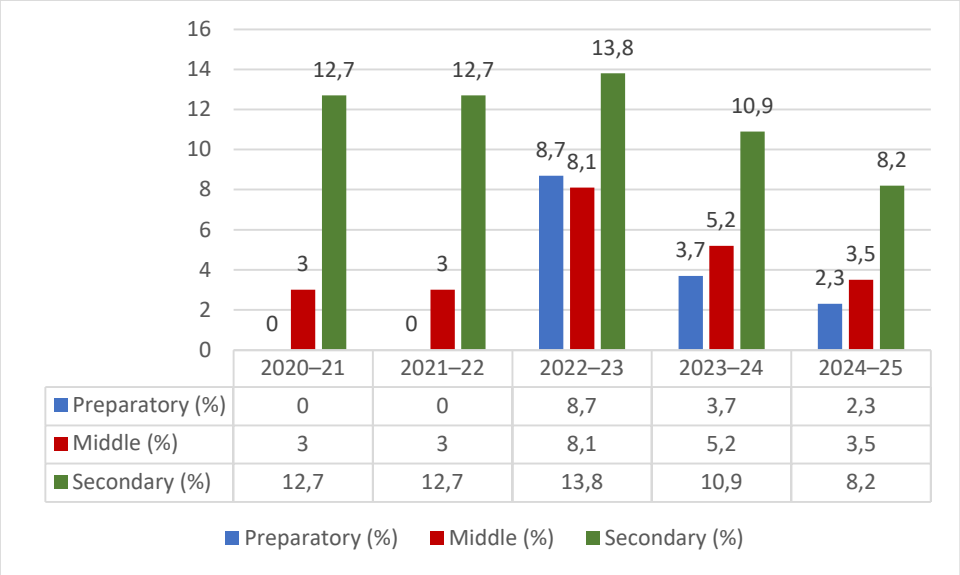
Table No. 1: represent the dropout data in different levels of Indian Schools

Academic Year	Primary / Preparatory (%)	Upper Primary / Middle (%)	Secondary (%)	Source
2020–21	NA	3.0	12.7	UDISE+/Rajya Sabha government release
2021–22	NA	3.0	12.7	UDISE+/Rajya Sabha government release
2022–23	8.7 *(Preparatory, NEP structure)*	8.1 *(Middle)*	13.8	UDISE+ / Ministry of Education
2023–24	1.9 *(Primary)* / 3.7 *(Preparatory)*	5.2 *(Upper Primary / Middle)*	14.1 *(Secondary)* / 10.9 *(NEP stage)*	Economic Survey / UDISE+

2024–25	0.3 *(Primary)* / 2.3 *(Preparatory)*	3.5	11.5 *(school-level release)* / 8.2 *(NEP stage release)*	UDISE+ / PIB

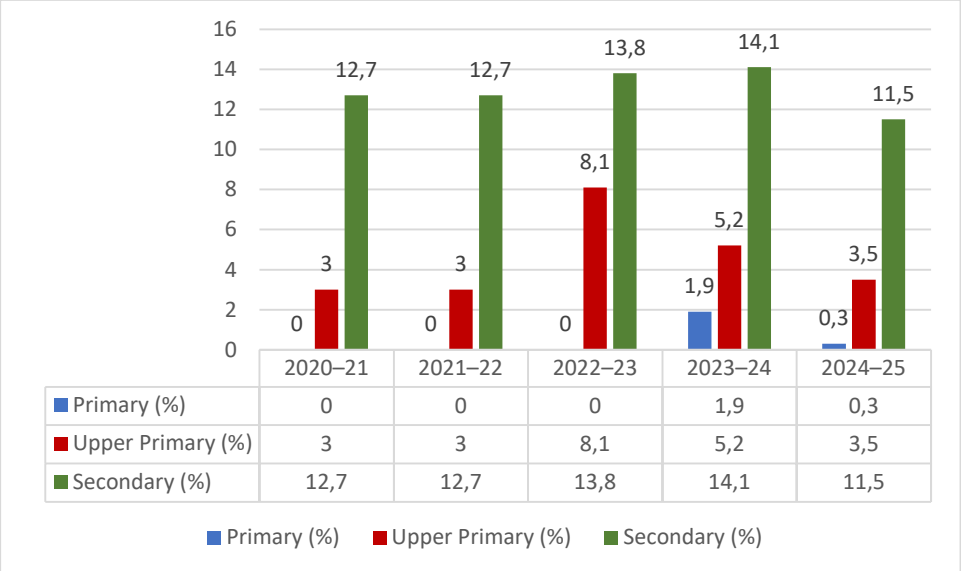
Source: UDISE+/Rajya Sabha government release, UDISE+ / Ministry of Education, Economic Survey / UDISE+

Graph-2 Represent Trends in Student Dropout Rates Across Educational Stages in India (2020–25)



Source: UDISE+/Rajya Sabha government release, UDISE+ / Ministry of Education, Economic Survey / UDISE+

Graph-3 Using School-Level (Primary–Upper Primary–Secondary)



Source: UDISE+/Rajya Sabha government release, UDISE+ / Ministry of Education, Economic Survey / UDISE+

Risk Identification:

The effectiveness of an Early Warning System (EWS) in education depends significantly on its ability to accurately identify, communicate, and respond to learner risk through a structured and evidence-based framework. The process of risk identification is central to this system and involves the systematic use of academic, behavioural, and contextual data to detect early signs of vulnerability among learners [5,13,14]. In practice, risk identification may occur through predefined thresholds such as attendance below 75%, cumulative risk scoring models, teacher-generated alerts, statistical analyses, or advanced machine learning-based forecasting techniques [9,20]. These approaches allow institutions to move beyond subjective judgment toward data-informed decision-making.

Research in learning analytics strongly supports the predictive potential of early behavioural indicators. Akçapınar et al. demonstrated that learner engagement patterns at the beginning of a course—such as login frequency, participation, and assignment submission—can effectively predict end-of-course outcomes [5]. This finding highlights that institutions need not wait until final examinations to recognize academic risk. Instead, early-stage data can provide actionable insights, enable timely identification of vulnerable learners and reduce the likelihood of late intervention [14,15].

Once risk is identified, the next critical stage is alert generation. An effective EWS must ensure that relevant stakeholders are informed in a timely and structured manner. These stakeholders typically include class teachers, mentors, counsellors, academic advisors, department heads, and, in school contexts, parents or guardians [16,17]. In some models, learners themselves are also notified, encouraging self-regulation and responsibility in the learning process. The purpose of alert generation is not merely to communicate risk but to initiate a coordinated institutional response aimed at learner support [6,18].

Intervention represents the most crucial and impactful component of the EWS framework. Without meaningful and timely intervention, risk identification remains only a diagnostic exercise. Bañeres et al. emphasized that predictive systems achieve educational value only when they are directly linked to targeted and personalized interventions [6]. These interventions may take multiple forms depending on the nature and severity of the risk. Academic mentoring and remedial

teaching are commonly used to address learning gaps, while attendance counselling and parental engagement help improve participation and accountability [11,12]. Peer support systems can enhance motivation and belongingness, whereas digital access assistance is essential in contexts affected by technological inequality [17,18]. Additionally, emotional and psychological support, including counselling referrals, plays a vital role in addressing non-academic barriers to learning [8,18]. Flexible academic planning, such as adjusted timelines or alternative learning pathways, further supports learners facing complex challenges [10].

The identification of at-risk learners in India requires particular attention to context-specific indicators. A robust EWS must integrate both academic performance metrics and structural dimensions of disadvantage [10,11]. Indicators such as irregular attendance, declining academic performance, and low classroom or digital participation remain fundamental [5,15]. However, in the Indian context, these must be complemented by factors such as socio-economic background, first-generation learner status, rural or remote location, language barriers, and access to digital resources [11,12,16]. National and international reports emphasize that such multidimensional indicators are essential for understanding the complex nature of learner vulnerability and ensuring equitable intervention strategies [16,17].

Moreover, advancements in educational data mining and artificial intelligence have enhanced the capacity of EWS to analyse both static and dynamic variables over time. Techniques such as decision trees, regression models, and ensemble learning approaches enable more accurate prediction of student attrition and disengagement [9,13,20]. These technologies allow institutions to continuously monitor patterns of behaviour rather than relying on one-time assessments, thereby improving the precision and effectiveness of risk identification.

In conclusion, risk identification, alert generation, and intervention form an interconnected framework that determines the success of Early Warning Systems in education. In the Indian context, the integration of diverse indicators and context-sensitive strategies is essential for addressing educational vulnerability. By combining data-driven insights with human-centered intervention, EWS offers a powerful approach to promoting student retention, engagement, and overall educational equity [5,16,17].

Identifying At-Risk Learners

A comprehensive Early Warning System (EWS) in education depends on the identification of multiple interrelated indicators that together reflect the academic, behavioural, and socio-

economic conditions of learners. In the Indian context, where educational risk is often gradual and multidimensional, these indicators must go beyond examination outcomes and incorporate patterns of engagement, participation, and contextual vulnerability [10–12,16]. Attendance is widely recognized as one of the most powerful early indicators of risk. Persistent or irregular absence is often associated with disengagement, family-related stress, health concerns, or socio-economic pressures. National datasets and policy analyses show that even where enrolment is high, actual participation may remain inconsistent, making attendance a critical signal of emerging vulnerability [11,12,16].

Academic performance is another key dimension, but contemporary research emphasizes the importance of identifying trends rather than isolated instances of low achievement. A gradual decline in internal assessments, class tests, and semester evaluations often reflects deeper learning gaps or disengagement, which may not be visible through a single examination score [5,14,15]. Similarly, assignment and task completion patterns provide strong predictive insights. Learners who consistently miss assignments, fail to participate in project work, or show irregular coursework engagement often exhibit early signs of academic withdrawal, which can later translate into failure or dropout [13–15].

With the expansion of blended and digital learning environments, digital participation has emerged as a crucial indicator. Patterns such as low frequency of learning management system access, minimal interaction with digital content, lack of participation in online discussions, and irregular attendance in virtual classes have been shown to correlate strongly with academic risk. Studies in learning analytics demonstrate that digital behaviour, particularly in the early stages of a course, can effectively predict long-term outcomes, thereby enabling early intervention [5,8,18]. This is particularly relevant in the post-pandemic Indian context, where disparities in access to digital infrastructure continue to influence learning continuity and engagement [16–18].

In addition to academic and behavioural indicators, socio-economic and contextual factors play a decisive role in shaping learner risk in India. Conditions such as being a first-generation learner, financial instability, lack of access to digital devices or internet connectivity, long commuting distances, migration-related disruptions, family responsibilities, and language transition challenges significantly affect student participation and progression [10–12,16,17]. These factors highlight that educational vulnerability is not merely an individual issue but is deeply embedded in broader structural inequalities.

Equally important are behavioural and psychosocial indicators, which are often not formally recorded but are critical for early identification. Signs such as sudden withdrawal from participation, reduced classroom interaction, visible stress, low confidence, and repeated requests

for deadline extensions may indicate underlying emotional or psychological challenges. Research in educational technology and learner analytics underscores the importance of integrating such qualitative observations with quantitative data to achieve a more accurate understanding of student risk [8,18].

Therefore, an effective EWS in India must adopt a holistic and integrated approach that combines measurable indicators with teacher observations and contextual awareness. Advances in machine learning and predictive analytics further enhance the ability to track both static and dynamic variables over time, improving the precision of risk identification and enabling timely interventions [9,13,20]. By recognizing patterns of vulnerability early and responding proactively, institutions can shift from a reactive to a preventive model of education, thereby improving retention, equity, and overall learning outcomes [5,16,17].

9. Early Warning Systems in School Education in India

Early Warning Systems (EWS) hold significant potential in strengthening school education in India, particularly in addressing persistent challenges such as chronic absenteeism, poor foundational learning, transition-related risks, gendered discontinuity, and silent disengagement among learners. These issues are deeply embedded in the structure of Indian schooling and require systematic, preventive mechanisms rather than reactive responses [10–12,16]. Chronic absenteeism, for instance, is widely recognized as an early indicator of disengagement and is often linked with socio-economic pressures, household responsibilities, or lack of academic motivation. Research suggests that irregular attendance, when tracked consistently, can help institutions identify vulnerable learners long before they formally drop out [11,16].

Poor foundational learning is another critical concern, especially at the primary and upper-primary levels, where gaps in literacy and numeracy can accumulate over time and hinder progression. When such gaps remain unaddressed, learners face increasing difficulty in coping with higher-level curricula, leading to frustration, low confidence, and eventual withdrawal [11,12]. EWS can assist in identifying these learners early by monitoring assessment patterns and classroom participation, thereby enabling timely remedial interventions [5,14].

Transition stages, particularly from upper-primary to secondary education, represent a high-risk period for many students in India. During this phase, learners encounter increased academic demands, examination pressure, social expectations, and financial constraints. Official statistics consistently show that dropout rates are significantly higher at the secondary level, indicating that many students struggle to sustain engagement as they progress through the system [11,12]. EWS

can play a crucial role in detecting early warning signs during these transitions, allowing schools to provide targeted academic and emotional support [16,17].

Gendered discontinuity further complicates the issue, as social norms, safety concerns, and domestic responsibilities disproportionately affect girls' participation and continuity in education. These factors often remain invisible in formal data but contribute significantly to dropout and irregular attendance [16,17]. Similarly, silent disengagement—where students remain enrolled but gradually withdraw from active participation—poses a serious challenge. Such learners may attend classes irregularly, fail to complete assignments, and show minimal interaction, yet may not immediately appear in dropout statistics [11,12]. EWS helps in identifying these patterns through continuous monitoring of engagement indicators [5,15].

Importantly, the implementation of EWS in Indian schools does not necessarily require advanced artificial intelligence or complex technological infrastructure. Research in educational data systems indicates that even low-cost, school-based dashboards can be highly effective when used consistently [13,18]. Indicators such as attendance records, periodic test performance, teacher observations, homework completion, and parental follow-up provide sufficient data to identify early signs of risk [11,12]. When these indicators are systematically tracked and reviewed, they enable schools to take timely and informed action.

Such systems are particularly valuable in government schools, where a large proportion of students come from socio-economically disadvantaged backgrounds. In these settings, EWS can support coordinated efforts among teachers, school management committees, counsellors, and parents to address learner needs holistically [16,17]. Studies emphasize that the effectiveness of EWS depends not only on data collection but also on institutional responsiveness and collaborative intervention strategies [6,9].

In conclusion, EWS offers a practical and scalable solution for addressing key educational challenges in Indian school education. By focusing on early identification and timely intervention, even simple monitoring systems can significantly improve retention, engagement, and learning outcomes. This approach aligns with broader policy goals of equity, inclusion, and reduced dropout, reinforcing the need for widespread adoption of EWS in Indian schools [10,16,17]

Early Warning Systems in Higher Education in India

Early Warning Systems (EWS) are increasingly necessary in higher education in India, particularly at the undergraduate level particularly in rural area, where students often encounter

multiple adjustment challenges that affect their academic progression and retention. The transition from school to college represents a significant shift in learning environment, expectations, and responsibilities. Many students struggle with English-medium instruction, independent learning demands, unfamiliar disciplinary content, weak academic self-regulation, and limited access to structured mentoring support [10–12,16]. These challenges are especially pronounced among first-generation learners and those from diverse socio-economic backgrounds, making the first year of undergraduate education a critical period of vulnerability.

In many cases, students do not immediately express these difficulties but instead experience what can be described as "silent disengagement." They may continue attending classes irregularly, fail to actively participate, or gradually fall behind in coursework until academic backlogs accumulate or attendance drops significantly [11,12]. Research in learning analytics indicates that such behavioural patterns—low participation, irregular attendance, and incomplete coursework—are strong predictors of future academic risk and dropout [5,14,15]. Without systematic mechanisms for early identification, institutions often respond only after failure has occurred, reducing the effectiveness of remedial efforts.

Although India does not yet maintain a comprehensive, standardized dropout tracking system in higher education comparable to school-level databases, national frameworks such as the All-India Survey on Higher Education (AISHE) provide valuable insights into enrollment, progression, and participation trends [11]. These data highlight the scale, diversity, and complexity of the higher education system, where student needs vary widely across regions, disciplines, and institutional types. With the introduction of recent reforms such as the Academic Bank of Credits, multiple entry and exit options, and flexible degree pathways, the structure of higher education has become more dynamic and student-cantered [10]. While these reforms enhance flexibility and access, they also increase the need for continuous learner tracking and timely academic support, as students may move in and out of the system at different stages.

In this evolving context, EWS can serve as a critical institutional tool for supporting student success. Indicators used in higher education EWS typically include low attendance, non-submission of assignments, poor internal assessment performance, reduced participation in Learning Management Systems (LMS), repeated backlog accumulation, low credit completion rates, and minimal engagement with mentoring systems [5,13,20]. These indicators reflect both academic and behavioural dimensions of student engagement and can be monitored over time to detect emerging patterns of risk. Studies have shown that combining multiple indicators enhances predictive accuracy and allows institutions to design targeted interventions [5,9].

Digital participation, in particular, has become an important dimension of risk identification in higher education. Patterns such as infrequent LMS access, low engagement with online resources, and limited interaction in virtual discussions provide early signals of disengagement, especially in blended and online learning environments [8,18]. Similarly, the accumulation of academic backlogs and low credit completion rates are strong indicators of progression challenges, which, if unaddressed, may lead to dropout or delayed graduation [14,15].

EWS also plays a vital role in strengthening mentoring and student support systems within higher education institutions. Regular monitoring of student engagement allows mentors, faculty members, and academic advisors to identify at-risk learners and provide timely guidance, counselling, and academic assistance [6,9]. This shifts the institutional approach from reactive problem-solving to proactive support, fostering a more inclusive and responsive learning environment.

The implementation of Early Warning Systems in Indian higher education is essential for addressing the complex challenges faced by undergraduate students. By integrating academic, behavioural, and digital indicators, EWS enables institutions to identify vulnerability early and provide targeted interventions. This not only improves student retention and progression but also supports the broader goals of flexibility, inclusivity, and learner-cantered education envisioned in contemporary policy reforms [10,16,17].

Role of Learning Analytics and Educational Data Mining

The increasing prominence of learning analytics has significantly strengthened the development and application of Early Warning Systems (EWS) in education, particularly in identifying at-risk learners through data-driven insights. Learning analytics refers to the systematic collection, measurement, analysis, and interpretation of learner data to optimize learning processes and educational environments [7,13]. In digital and blended learning contexts, students continuously generate behavioural traces such as login frequency, clicks, resource access, participation in discussions, quiz attempts, and content viewing patterns. These digital footprints provide valuable insights not only into academic performance but also into patterns of engagement and disengagement, which are crucial for early risk detection [14,15].

Research has consistently demonstrated the predictive potential of such behavioural data. Akçapınar et al. showed that interaction data collected early in a course can effectively identify students at risk before final assessments, enabling timely intervention [5]. Similarly, Bañeres et al.

highlighted that artificial intelligence–driven systems can successfully detect disengaged learners in online higher education settings, provided these systems are coupled with appropriate pedagogical responses [6]. These findings are further supported by systematic reviews indicating that learning analytics can play a critical role in reducing dropout rates when institutions actively use data to support student persistence rather than merely record outcomes [8]. Advanced machine learning techniques, including ensemble models and predictive algorithms, have also been found to enhance the accuracy of identifying at-risk students by combining both static and dynamic variables [9,20].

However, the effectiveness of EWS should not be equated solely with technological sophistication. In the Indian context, where institutional diversity and resource constraints are significant, even basic analytics based on attendance trends, assessment performance, participation frequency, and submission patterns can be highly effective in identifying vulnerable learners [10–12]. Studies in broader early warning applications, including environmental and financial systems, also suggest that the success of such systems depends more on timely interpretation and response than on complexity alone [1,2,4]. Moreover, predictive analytics frameworks designed for online learners emphasize that the integration of early warning signals with structured intervention strategies is essential for meaningful educational outcomes [3].

Policy frameworks and international reports further reinforce the importance of data-informed educational practices. The National Education Policy 2020 emphasizes learner-centric approaches, inclusion, and reduced dropout, aligning closely with the principles of EWS [10]. Reports by UNESCO and UNICEF also advocate for systematic monitoring mechanisms to identify and support at-risk learners, particularly in contexts marked by inequality and disruption [16,17]. Additionally, research on artificial intelligence in higher education highlights the growing role of intelligent systems in enhancing student support, though it also calls for careful integration with pedagogical practices [18].

Ultimately, the value of Early Warning Systems lies not in their technological advancement but in their educational responsiveness. Whether through advanced machine learning models or simple institutional dashboards, the primary goal remains the same: to detect early signs of learner vulnerability and enable timely, meaningful intervention. In this sense, EWS represents a shift from reactive to proactive education systems, where the focus is on prevention, inclusion, and sustained learner engagement across diverse educational contexts [19].

Findings and Discussion

The review of literature, policy frameworks, and recent educational data highlights several interrelated findings regarding Early Warning Systems (EWS) in education, particularly in the Indian context**.**

India has a strong need for early identification of learner risk

Despite significant improvements in enrolment, national data continue to indicate challenges in retention, especially at the secondary level, as reflected in UDISE+ statistics and national education overviews published by the Ministry of Education, Government of India (12, 11). This suggests that India's current education system remains largely reactive rather than preventive in addressing student dropout and disengagement. International research also emphasizes that early detection mechanisms are critical to improving learner persistence and educational outcomes (17, 8).

At-risk status in India is multidimensional

The literature consistently demonstrates that student vulnerability cannot be explained solely by academic performance. Instead, it is shaped by a combination of attendance patterns, socio-economic constraints, language barriers, digital divide, and psychosocial factors (8, 14, 6). Studies in learning analytics and educational data mining further confirm that at-risk identification requires integrating multiple indicators rather than relying on a single metric (13, 7). This multidimensionality aligns with broader global findings in predictive education models and risk classification systems (9, 20).

Existing educational systems often identify risk too late

In many institutions, students are classified as "at risk" only after academic failure, backlog accumulation, or prolonged absenteeism. This reflects a post-failure identification model rather than a preventive intervention framework (6, 14). Literature on dropout prevention in higher education highlights that delayed identification significantly reduces the effectiveness of remedial interventions (8, 15). UNICEF (17) similarly emphasizes that early detection is essential to preventing permanent disengagement from education systems.

Early Warning Systems can be built with both high-tech and low-tech models

Contrary to the assumption that EWS requires advanced artificial intelligence infrastructure, research demonstrates that even simple indicators such as attendance records, classroom participation, and continuous internal assessment can form effective early warning mechanisms (6,

19). While machine learning and ensemble models enhance predictive accuracy (9, 20), foundational systems based on structured observation remain highly relevant in resource-constrained educational contexts like India.

Prediction without intervention is educationally incomplete

Finding across studies is that predictive analytics alone is insufficient unless linked with structured interventions. Bañeres et al. (6) explicitly argue that EWS must function as both a detection and response mechanism. Similarly, literature on learning analytics highlights that actionable insights must be translated into mentoring, counselling, and remedial academic support to improve student outcomes (8, 5). Without intervention pathways, predictive systems lose educational value.

NEP 2020 creates a favourable policy environment

The National Education Policy 2020 strongly supports inclusive, flexible, and student-centred learning pathways, which align closely with the philosophy of EWS (10). Policy documents, including the Economic Survey and UDISE+ reports, further reinforce the need to reduce dropout rates and improve retention through systemic reforms (11, 12). This policy environment provides a strong institutional foundation for integrating EWS into Indian schools and higher education systems.

Challenges in Implementing EWS in India

Despite the strong theoretical and policy support for Early Warning Systems (EWS) in education, their implementation in India faces multiple structural, pedagogical, and ethical challenges. These challenges must be understood in relation to institutional capacity, digital equity, and intervention readiness.

Data fragmentation

One of the most significant barriers is the fragmentation of student data across institutions. Attendance, assessment, behavioural records, and participation data are often stored in separate, non-integrated systems. This lack of interoperability makes it difficult to develop a unified learner profile for predictive analysis. Literature on learning analytics consistently emphasizes that effective EWS requires integrated data ecosystems and standardized data pipelines (7, 13, 8). In the absence of such integration, predictive accuracy and system reliability are significantly reduced (6, 14).

Unequal digital access

Another major challenge is the digital divide, particularly in rural and economically disadvantaged contexts. Over-reliance on digital behaviour indicators (such as LMS logins or online participation) may misclassify students who lack access to digital infrastructure as "at risk," even when their academic engagement is adequate in offline settings (16, 17). Studies on educational inequality highlight that digital exclusion can distort predictive analytics and reinforce existing inequities if not carefully contextualized (8, 11).

Teacher workload and capacity constraints

The success of EWS depends heavily on teachers' ability to interpret dashboards and respond to risk signals. However, in many Indian schools and colleges, teachers already face high workloads, limiting their capacity to engage with additional analytical tools. Research indicates that without adequate training and institutional support, learning analytics tools remain underutilized or misinterpreted (5, 18). Effective implementation therefore requires professional development and simplification of dashboard interfaces (6, 9).

Risk of labelling and stigma

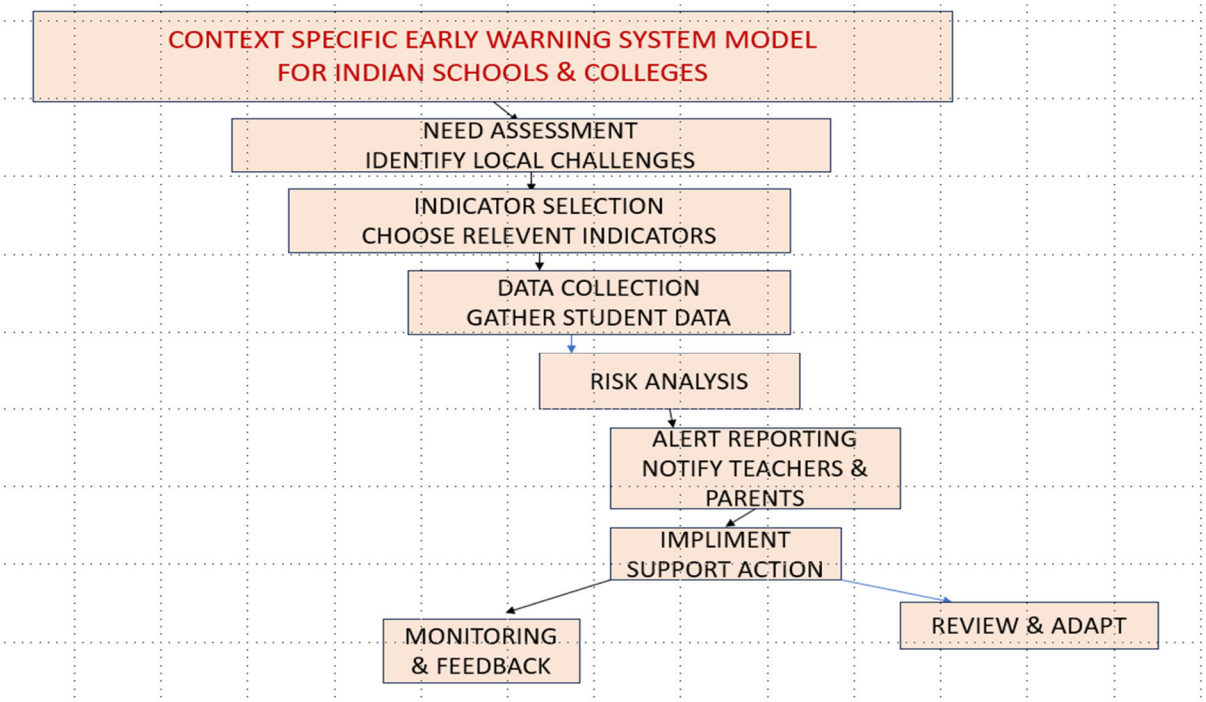
A critical ethical concern is the potential for labelling students as "at risk," which may unintentionally lead to stigma and reduced teacher expectations. Studies in educational psychology warn that predictive categorization without sensitive communication strategies can negatively affect student identity and motivation (17, 14). UNICEF (17) emphasizes that early warning mechanisms must prioritize supportive language and confidentiality to avoid reinforcing marginalization.

Weak intervention infrastructure

Perhaps the most significant implementation barrier is the lack of robust intervention systems. While EWS can identify vulnerable learners, many institutions lack sufficient counsellors, mentors, or structured remedial programs to act on these alerts (6, 8). Literature consistently highlights that predictive systems without intervention pathways fail to produce meaningful educational improvement (5, 15). This gap between detection and response remains a major limitation in developing countries' education systems (12, 19).

Raching the Ultimate Process of Context-Specific EWS Implementation

IMAGE -1 Repesent the Contextual Early Warning System Model (CEWSM)



Source: Developed by Investigator

The proposed model operates as a dynamic and iterative system that moves from identification to intervention and finally to continuous refinement. The ultimate goal is not merely early detection of at-risk learners, but the creation of a responsive, inclusive, and sustainable educational support system.

The process begins with Needs Assessment, where institutions identify their local realities, including socio-economic conditions, digital access, language diversity, and institutional capacity. This ensures that the system is grounded in context rather than borrowed from external models.

This is followed by Indicator Selection, where relevant and measurable indicators such as attendance, academic performance, engagement levels, and socio-emotional signals are chosen. The accuracy of the system depends heavily on selecting indicators that reflect real student vulnerabilities.

In the Data Collection phase, institutions systematically gather student data through both digital and manual means. This stage emphasizes regularity, reliability, and inclusivity of data, ensuring that no student group is overlooked.

The next stage, Risk Analysis, transforms raw data into meaningful insights. Through simple analytics or advanced models, patterns of disengagement and vulnerability are identified early, allowing institutions to shift from reactive to proactive approaches.

Once risks are identified, Alert and Reporting mechanisms ensure that relevant stakeholders—teachers, mentors, counsellors, and parents—are informed in a timely manner. This creates a shared responsibility framework within the institution.

The most critical stage is Intervention Strategies, where targeted support such as remedial teaching, mentoring, counselling, or financial and digital assistance is provided. The effectiveness of the entire model depends on the quality and timeliness of these interventions.

Subsequently, Monitoring and Feedback tracks student progress after intervention, assessing whether the support has improved engagement and performance. This ensures accountability and evidence-based decision-making.

Finally, the process culminates in Review and Adaptation, where the system is continuously refined based on outcomes, challenges, and feedback. This transforms the model into a self-improving ecosystem.

Educational Implications and Recommendations

Based on the present analysis of literature, policy frameworks, and educational data, several recommendations emerge for strengthening Early Warning Systems (EWS) in India in a more practical, ethical, and policy-aligned manner. A key recommendation is that institutions should begin EWS implementation with simple and readily available indicators such as attendance records, internal assessment scores, assignment completion rates, and classroom participation. These indicators are cost-effective, easy to collect, and highly relevant in identifying early signs of academic disengagement. Existing research in learning analytics and educational data mining supports the view that even basic data sources, when systematically organized, can provide reliable signals for identifying at-risk learners without requiring advanced technological infrastructure [3, 13, 15]. This makes the approach particularly suitable for diverse Indian educational settings where digital maturity varies widely.

Another essential recommendation is the integration of EWS with structured mentoring systems. The effectiveness of any early warning mechanism depends not only on detection but also on timely human intervention. Therefore, every risk signal generated by the system should

automatically trigger a mentor–mentee response loop, ensuring that students receive personalised academic guidance, emotional support, and remedial assistance. Literature consistently highlights that predictive models alone are insufficient unless they are directly linked to actionable interventions that improve student outcomes [5, 8]. In this sense, teachers and mentors become central agents in transforming data insights into meaningful educational support rather than passive observers of risk dashboards [6, 15].

A further recommendation is the inclusion of socio-economic sensitivity within EWS interpretation frameworks. Student risk must not be understood purely as an individual academic issue but as a reflection of broader structural inequalities. Factors such as poverty, first-generation learning status, language barriers, and limited access to digital resources significantly shape student engagement and performance. Research shows that without contextual interpretation, data-driven systems may unintentionally misclassify disadvantaged learners as academically weak, thereby reinforcing inequality rather than reducing it [11, 16]. Therefore, EWS must incorporate socio-economic context as a core analytical dimension to ensure fairness and accuracy in decision-making [8, 17].

It is also important that EWS implementation is aligned with the National Education Policy 2020 and institutional quality assurance frameworks. NEP 2020 strongly emphasizes equity, retention, flexibility, and student support, which directly correspond to the objectives of early warning systems [10]. Integrating EWS into institutional monitoring processes, quality audits, and student progression systems can ensure long-term sustainability and policy coherence. National reports such as the Economic Survey and UDISE+ also reinforce the importance of improving retention and reducing dropout rates through systematic and data-informed interventions [12, 20].

In addition, protecting privacy and dignity must remain a central ethical requirement in any EWS framework. The use of student data must be governed by clear principles of consent, confidentiality, and responsible data handling. International literature on learning analytics emphasizes that ethical safeguards are essential to maintain trust and prevent misuse of predictive systems [16, 18]. Students should never be stigmatized or labelled negatively based on algorithmic predictions, as this can harm motivation and self-perception [17].

To operationalize these recommendations, this study proposes an integrated "Contextual Early Intervention System Model (CEISM)". The model consists of four interconnected layers: data collection (simple indicators from academic and behavioural records), risk identification (rule-based or basic analytic scoring), contextual interpretation (teacher and institutional review

considering socio-economic background), and intervention response (mentor-led support, counselling, and remedial action). The model ensures that prediction is always followed by human judgment and structured support, making EWS both practical and ethically grounded.

Early Warning Systems in India must evolve as inclusive, low-cost, and intervention-driven frameworks. When grounded in simple indicators, human mentorship, socio-economic sensitivity, policy alignment, and ethical safeguards, and supported by models such as CEISM, EWS can transform from a monitoring tool into a comprehensive student support ecosystem that promotes equity, retention, and educational success [10, 11, 16].

Conclusion

Early Warning Systems (EWS) represent a fundamental shift in educational thinking, moving away from reactive approaches that manage student failure after it occurs toward proactive systems that identify and support learners before failure happens. This transformation is especially significant in the Indian education system, where student vulnerability often develops gradually and remains unnoticed until it manifests as poor performance, absenteeism, or dropout. Research in learning analytics and educational data mining consistently emphasizes that early detection of risk factors is crucial for improving student retention and academic success [3, 13, 15]. In this context, EWS provides a structured mechanism to identify subtle patterns of disengagement that traditional evaluation systems may overlook.

In India, the need for such systems is particularly urgent due to persistent challenges at the secondary education level, where dropout rates and irregular attendance remain significant concerns. National datasets such as UDISE+ and policy analyses from the Ministry of Education highlight continued disparities in retention and progression across regions and socio-economic groups [11, 12]. Additionally, issues such as digital inequality, language diversity, and uneven access to learning resources further contribute to educational vulnerability. International research also supports the view that student risk is multi-causal and evolves over time rather than resulting from a single academic failure event [8, 16]. Therefore, EWS becomes an essential tool for identifying cumulative risk patterns rather than isolated performance gaps.

The literature further demonstrates that Early Warning Systems are not merely technological tools but integrated educational frameworks that combine data analytics with institutional response mechanisms. Studies in learning analytics highlight that predictive systems alone have limited value unless they are connected to timely interventions such as mentoring, counselling, and academic

support [5, 6]. This reinforces the idea that EWS is not only about identifying at-risk students but also about ensuring that institutions are prepared to respond effectively and empathetically. Without such intervention structures, EWS risks becoming a diagnostic system without educational impact [8, 15].

In the Indian context, EWS also reflects a broader pedagogical and institutional responsibility. The National Education Policy 2020 emphasizes equity, inclusion, and student support as core principles of educational reform, which align closely with the objectives of early warning systems [10]. Integrating EWS into institutional quality assurance frameworks and student progression monitoring systems can therefore strengthen accountability while improving learner outcomes. Furthermore, national reports such as the Economic Survey and UDISE+ underline the importance of reducing dropout rates and improving learning continuity through systematic reforms [12, 20].

Importantly, the true value of EWS lies not in its ability to classify students but in its capacity to enable timely, sensitive, and context-aware responses. Research consistently warns against the risk of labelling students in ways that may lead to stigma or reduced expectations, highlighting the need for ethical safeguards in data use and interpretation [16, 17]. EWS must therefore be implemented with strong attention to privacy, dignity, and socio-economic context to ensure that it supports rather than disadvantages vulnerable learners.

Ultimately, when implemented thoughtfully, Early Warning Systems can help Indian educational institutions transition toward a more equitable and responsive model of education. Such a system would ensure that vulnerable learners are identified early, supported appropriately, and provided with opportunities to succeed before they reach a point of academic failure. In doing so, EWS transforms education from a reactive system of correction into a proactive system of continuous support and inclusion, aligning both with global best practices and India's evolving educational priorities [10, 11, 16].

References

1. Fasan M, Scarpa F, Flores E. Early warning systems for financial distress: international developments. Rev Educ Pesqui Contab. 2026;20.
2. Biswas U, Mahato S, Joshi PK. Spatial prediction of forest fires in India: a machine learning approach for improved risk assessment and early warning systems. Environ Sci Pollut Res. 2025;32(8):4856–4878.
3. Dunsin D. Early warning systems for online learners using predictive analytics. 2023.
4. de Valk G, Vaandrager D. Operation Canthi: On merging early warning, early response, system analysis, and deep learning. Natl Secur Future. 2026;27(1):59–109.
5. Akçapınar G, Altun A, Aşkar P. Using learning analytics to develop early-warning system for at-risk students. Int J Educ Technol High Educ. 2019;16(1):40.
6. Bañeres D, Rodríguez ME, Guerrero-Roldán AE, Karadeniz A. An early warning system to detect at-risk students in online higher education. Appl Sci. 2020;10(13):4427.
7. Chatti MA, Dyckhoff AL, Schroeder U, Thüs H. A reference model for learning analytics. Int J Technol Enhanc Learn. 2012;4(5–6):318–331.
8. de Oliveira CF, Sobral SR, Ferreira MJ, Moreira F. How does learning analytics contribute to prevent students' dropout in higher education: a systematic literature review. Future Internet. 2021;13(11):287.
9. Jimenez Martinez AL, Sood K, Mahto R. Early detection of at-risk students using machine learning. arXiv. 2024.
10. Ministry of Education, Government of India. National Education Policy 2020. New Delhi: Government of India; 2020.
11. Ministry of Education, Government of India. Economic Survey 2024–25: education overview and school dropout indicators. New Delhi: Government of India; 2025.
12. Ministry of Education, Government of India. UDISE+ 2024–25 and 2023–24 school education statistics. New Delhi: Government of India; 2025.
13. Peña-Ayala A. Educational data mining: a survey and a data mining-based analysis of recent works. Expert Syst Appl. 2014;41(4):1432–1462.
14. Queiroga EM, Cechinel C, Araújo RM, Sicília MÁ. A learning analytics approach to identify students at risk of dropout: a case study with a technical distance education course. Appl Sci. 2020;10(11):3998.
15. Romero C, Olmo JL, Ventura S. Predicting student final performance from participation in online discussion forums. Comput Educ. 2013;68:458–472.

16. UNESCO. State of the education report for India 2024: Rhythms of learning. Paris: UNESCO; 2024.
17. UNICEF. Early warning systems for students at risk of dropping out. New York: UNICEF; 2018.
18. Zawacki-Richter O, Marín VI, Bond M, Gouverneur F. Systematic review of research on artificial intelligence applications in higher education—Where are the educators? Int J Educ Technol High Educ. 2019;16(1):39.
19. Mohanty A, Dubey A, Singh RB. The application of early warning system in India. In: Cyclonic disasters and resilience. 2022.
20. Arifudin MA, Setiana E, Nugraha AB. Ensemble learning for early warning systems in higher education: a comparative study of student attrition. Bull Intell Mach Algorithms. 2026;1(3):101–110.