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COMMENT

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Using routine school data to support adolescent well-being in resource-limited settings

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Abstract
Artificial intelligence (AI) is increasingly promoted as a tool to strengthen health systems, yet its use in low- and middle-income countries (LMICs) remains largely concentrated in hospitals and specialized settings, overlooking schools that reach most adolescents and often represent the first point where changes in health and well-being become visible. Despite routinely collecting data on attendance, meals, and basic health indicators, schools rarely use this information for prevention or early action. This paper presents a conceptual and practice-oriented framework for using routine school data to support early identification of emerging adolescent health risks. We describe a workflow that standardizes fragmented and partially digitized records and applies lightweight, task-specific AI-supported tools to detect patterns and deviations that may warrant attention, including in settings with intermittent data collection and limited digital infrastructure. The approach prioritizes low complexity, minimal infrastructure requirements, and integration into existing school routines, with outputs serving as advisory signals to support contextual interpretation by educators and school health staff. We emphasize that these signals are based on proxy indicators and require careful human review to avoid misinterpretation. We argue that school-level, privacy-preserving AI can strengthen prevention by enabling more timely, context-sensitive, and community-led responses, while its effectiveness depends on data quality, local capacity, and appropriate governance to ensure ethical use, transparency, and trust across diverse LMIC contexts.

Key message

- Schools in LMICs collect small but valuable data that can support early prevention when used systematically.
- Simple, explainable AI tools can help educators identify emerging health risks without replacing human judgment.
- School-level, privacy-preserving approaches can strengthen prevention, but their effectiveness depends on data quality, contextual interpretation, local capacity, and appropriate governance.

Keywords Artificial intelligence, School health, Adolescent well-being, LMICs, Digital public health, Ethics

1 Introduction

Artificial intelligence (AI) has become an important part of modern health systems, offering the promise of prediction, personalization, and efficiency. Yet in many low- and middle-income countries (LMICs), AI in health remains focused on hospitals, diagnostics, and electronic records, far removed from where young people actually live and learn [1–3]. Schools are almost absent from this conversation, even though they reach nearly every child and often serve as the first link between health and community life. In most LMICs, school health programs are still paper-based and reactive, focused mainly on screenings or hygiene campaigns rather than prevention or data-informed action [4, 5].

The health challenges facing adolescents have changed profoundly. Across regions, mental health problems, malnutrition, and behavioral disorders now account for a growing share of adolescent disability-adjusted life years, overtaking infectious diseases in many countries [2, 5, 6]. These conditions often emerge first in classrooms, not clinics. Yet the data needed to respond remain fragmented and outdated, leaving educators and health systems unaware of early warning signs [1, 7].

AI offers a chance to change this, not by introducing complex predictive models, but by turning small, existing datasets into sources of local knowledge. With thoughtful design, AI can help teachers and school health officers detect trends, anticipate problems, and act early, even when resources are limited [7]. While existing literature describes broad opportunities for digital health in LMICs, this paper highlights a specific and often overlooked point: that the simple, small datasets already collected by schools can serve as the most actionable entry point for preventive adolescent health.

2 The data we already have

This section aims to demonstrate how small, routinely collected datasets in LMIC schools can provide insights and serve as practical entry points for AI-supported analysis. School infrastructure in LMICs varies substantially, particularly in terms of access to electricity, internet connectivity, and availability of digital devices. Globally, while approximately 69% of primary schools have access to electricity, this proportion falls to around 34% in least developed countries, with even lower rates reported in some regions such as sub-Saharan Africa [8]. Similarly, disparities in internet connectivity remain pronounced: only about 16% of primary schools in least developed countries have internet access [8]. At the population level, these inequalities are even more striking, with only around 6% of children in low-income countries having internet access at home compared to 87% in high-income settings [9]. While some schools operate with intermittent internet access and basic computing tools, others remain predominantly paper-based with limited or no digital infrastructure. These disparities reflect broader structural inequalities in education systems, where lack of electricity and connectivity directly constrains the ability to collect, digitize, and use educational data effectively [10]. In such contexts, variation in infrastructure is a key determinant of whether routine records can be consolidated and analyzed longitudinally. As such, the approach proposed in this paper is most applicable to schools with at least minimal operational capacity for periodic data digitization, including access to a basic computing device and intermittent electricity, even if internet connectivity is limited or inconsistent.

Despite these variabilities in infrastructure, schools in most LMICs routinely collect administrative and health-related information, such as attendance logs, basic growth monitoring, immunization status, hygiene checklists, and school meal participation. However, these datasets are rarely integrated or analyzed longitudinally [4, 11–14]. Studies of routine health information systems show that data are often fragmented and disorganized, with widespread concerns about timeliness, completeness, and representativeness, reflecting broader structural constraints in LMIC settings such as uneven digital infrastructure, partial digitization, and limited capacity to integrate data across sources [13, 15–17]. Many LMICs operate multiple parallel information systems driven by donor requirements, creating duplicated records and conflicting data that cannot be validated or synthesized across sources [11]. As a result, information remains underused, limiting schools' ability to notice early shifts in student well-being.

Routine school datasets contain early and often overlooked signals of adolescent health risks. Patterns such as frequent absences, changes in meal participation, or declining physical performance can point to early signs of stress, food insecurity, or poor nutrition [18]. When these indicators are examined over time, they form a potential early-warning system that is rarely leveraged in routine school practice. Schools are among the most consistent points of contact for children and adolescents and therefore uniquely positioned to detect early shifts in well-being [4].

Evidence from LMIC schools supports this potential. In the Philippines, a mobile-based attendance system using face-tagging technology improved the accuracy and reliability of attendance reporting and reduced errors associated with manual or Radio Frequency Identification-based recording, demonstrating that simple digital tools can strengthen routine school records when integrated into everyday workflows [19]. A similar example comes from Kenya, where the Tap2Eat digital wristband system records meal uptake and attendance in real time, enabling schools to identify declines in participation and adjust meal provision accordingly [20]. In Vietnam, pilot initiatives have applied AI models to routinely collected learning management system (LMS) data, analyzing student interactions with learning tasks to generate personalized recommendations, such as identifying knowledge gaps, suggesting supplementary materials, and adjusting study pathways [21]. These systems also draw on historical assessment and question bank data to predict areas where students may require additional support. However, such technologies are not uniformly available across LMIC school contexts and may still entail additional investment and implementation capacity that are not universally available.

Evidence from education and routine information systems more broadly supports the use of structured, low-complexity analytics to improve data use in resource-constrained settings. UNICEF guidance frames early warning systems as tools that use observable "red flags" to identify students who may require additional support, reinforcing the relevance of routine indicators such as attendance, participation, and performance [22]. In Guatemala, a large-scale early warning system for school dropout prevention used routinely available administrative data to identify students at risk and guide targeted support, demonstrating that school-level records can be operationalized for preventive action when embedded within existing education systems [23]. In Zimbabwe, a modular AI-supported platform integrated with DHIS2 and electronic health records reduced data-cleaning time, improved report timeliness, and eliminated critical data errors [24]. This demonstrates that lightweight automation can address practical data problems, such as error detection, harmonized reporting, and timely synthesis, that are similar to those faced by schools managing fragmented routine records.

In many LMIC settings, the more limiting gap is not data generation itself but the tools, capacity, and governance required to interpret routine indicators reliably across classes, terms, and schools [12, 13]. Lightweight, interpretable AI-supported tools can help fill this "missing middle" by automating routine analytical tasks, such as anomaly detection and basic trend analysis in longitudinal school data. While similar analyses can be performed using classical statistical approaches, these often require pre-specified rules and periodic technical input, which may be difficult to sustain in resource-constrained school settings. In contrast, such tools can operate continuously and adapt to individual patterns over time, helping to surface meaningful deviations that may warrant further attention. In line with World Health Organization (WHO)'s guidance that AI in resource-limited settings should prioritize safety, interpretability, and low-complexity applications [25], these tools can support schools in shifting from passive record-keeping to early prevention.

3 How small-data adds value in LMIC schools: a practical workflow

Building on this potential, a small-data workflow helps operationalize routine indicators into actionable signals. Before any analytic task is possible, the information collected by schools should be organized into a consistent structure, as these school datasets are typically small, longitudinal, and drawn from multiple sources, and routine indicators are sometimes recorded differently across classes or terms. For example, dates may be recorded in different formats, units for height or weight may vary, and attendance may be coded inconsistently, with missing entries where daily records were not completed. Creating a unified format for data types, timestamps, and reporting frequency provides the minimum foundation needed for any analytic tool to function reliably. In lower-resource settings, this step may involve simple, periodic digitization of paper records into basic spreadsheet formats. When these records are standardized, they can be analyzed together as a coherent timeline rather than as disconnected lists, using simple steps like filling small gaps or matching records from different lists so the timeline stays usable without needing complicated processing.

The next step is to apply lightweight, interpretable AI-supported tools that automates routine checks, minimizing the need for new data entry and additional staff capacity, although some initial setup and ongoing support may still be required. In this context, AI embedded within routine data systems. These include (1) rule-based and anomaly detection modules used to identify inconsistent or missing records, (2) automated data cleaning and validation workflows, and (3) semi-automated reporting tools integrated within platforms. A modular AI-supported system (OMDIP) incorporated a data diagnostic module for error detection, automated reporting tools, and analytics dashboards integrated with routine health information systems, resulting in substantial improvements in data quality, timeliness, and reporting efficiency [24]. Instead of complex prediction models, schools benefit from tools that scan for early shifts, such as gradual increases in absences, slow declines in meal participation, or repeated missed hygiene checks, that might be overlooked when staff only see one register at a time. For example, in a typical lower-secondary school setting where attendance and meal participation are recorded daily and digitized weekly, such models can establish each student's usual patterns over time. These tools can operate with minimal infrastructure and summarize their outputs as short lists of students, classes, or time periods that warrant closer review, which can then be discussed during routine staff meetings. Their purpose is not to diagnose or classify, but to support decision-making by highlighting patterns that merit follow-up. A two-week pattern of reduced attendance and skipped meals may be flagged as a deviation from an individual student's baseline, even if each individual absence remains below a fixed threshold. These signals can then be incorporated into routine staff discussions, where teachers and school health staff interpret the findings in context and determine appropriate follow-up actions.

Finally, the workflow requires translating signals into action in a safe and privacy-preserving way. Rather than pooling data at district level, privacy-first practices, such as sharing only aggregated summaries rather than student-level data, allow schools to contribute to broader insights while maintaining local control. The output of the system remains advisory: teachers and school health staff review alerts and decide whether they indicate a need for conversation, follow-up, or additional support. In this way, AI aims to support existing school processes by making routine information easier to interpret and act upon, while being designed to minimize additional burden on staff and uphold strong privacy protections.

To remain adaptable across diverse LMIC settings, the workflow specifies the functional properties of the analytic tools. This ensures that schools can adopt approaches compatible with their technical capacity, regulatory environment, and available data. In practice, implementation depends on basic feasibility factors, including variation in data completeness, limited digital literacy among staff, and uneven access to devices or connectivity, which may shape how frequently data are digitized and analyzed. In some cases, analytic tools would be pre-configured or supported by external developers or system-level actors, with schools primarily acting as end-users. Table 1 summarizes

Table 1 .AI-supported tool options for analyzing routine school data across different levels of digital capacity

Level of digital capacity	Typical school data environment	Example tools	Key capabilities
Basic (low-resource/paper-dominant)	Mostly paper-based records; intermittent digitization (e.g., periodic entry into spreadsheets)	Microsoft Excel, Google Sheets	Basic trend analysis, simple anomaly detection (e.g., thresholds, rolling averages)
Intermediate (transitional/partially digitized)	Mixed paper and digital systems; routine data available in spreadsheets or simple databases	Orange Data Mining, WEKA, KNIME (free/open-source)	Clustering, anomaly detection, basic time-series analysis
Advanced (digitally enabled settings)	Fully digitized records; some technical support available; integration with data platforms (e.g., EMIS, DHIS2)	Python (scikit-learn), Jupyter Notebook; integration with DHIS2 or KoboToolbox	Flexible modeling; automated analysis; integration across datasets

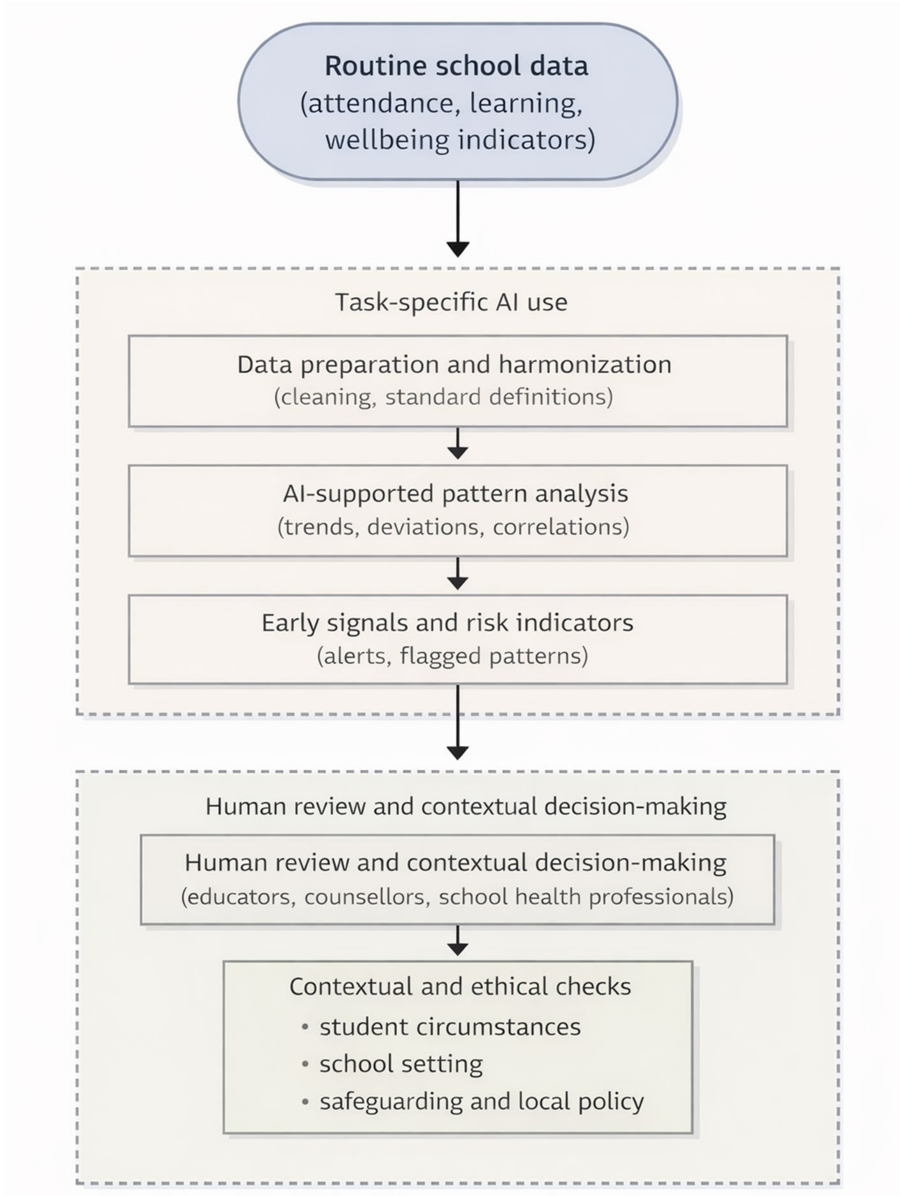

Fig. 1 AI-supported workflow for school health in LMICs

example tool options aligned with varying levels of digital capacity, along with their key capabilities [16, 26–31].

This workflow is illustrated in Fig. 1, which summarizes how standardized school data, AI-assisted analytic tools that enable adaptive pattern detection beyond rule-based methods, and human review interact to support early, school-led responses.

Figure 1 illustrates a practical, small-data workflow for the use of routine school data in low- and middle-income country (LMIC) school settings. Routinely collected indicators, such as attendance, learning participation, and basic wellbeing measures, are first standardized to ensure consistency across classes, time periods, and data sources. Task-specific AI tools are then applied to support pattern analysis, such as identifying trends, deviations, or recurring changes across indicators, and to surface early signals that may warrant attention.

All signals generated by the analytic layer are subject to human review by educators, counsellors, or school health professionals, who interpret findings in light of students' lived circumstances, school context, and local safeguarding policies. Contextual and ethical checks ensure that alerts are not interpreted mechanistically and that structural factors, such as economic constraints or resource limitations, are considered. Decision-making remains human-led at all stages, with AI functioning solely as a background support to reduce analytic burden and highlight patterns that may otherwise be overlooked.

4 Protecting trust while building technology

The power of AI comes with serious ethical responsibilities. School health data are deeply personal, especially when they involve children. In LMICs, where data protection laws are still evolving, these vulnerabilities can easily lead to unintended harm [7, 32]. The main question is not whether AI works, but whether it reflects fairness and care. Algorithms built on biased or incomplete data can reinforce inequality [33, 34].

In small-data settings, these risks are amplified, as limited or noisy inputs may lead AI systems to generate hallucinated interpretations: plausible but unsupported inferences that overstate risk or misclassify normal variation. Similar issues have been observed in real-world AI-based student monitoring systems, where behavioral signals may be over-interpreted and generate false positives, including cases where joking or exploratory student inputs are flagged as serious risk alerts requiring subsequent human verification [35]. Without strong safeguards, AI tools could label normal behavior as risky, stigmatize already marginalized groups, or allow surveillance to replace trust [36].

In practice, AI-driven early warning systems for student mental health rely on behavioral and engagement signals drawn from routine school or digital learning data, such as participation patterns, assignment submission, or interaction frequency. While these signals may indicate emotional distress, disengagement, or isolation, they remain indirect proxies rather than clinical measures; accordingly, such systems should be used to flag patterns for follow-up rather than to generate diagnostic conclusions [37].

Changes in attendance or participation, for example, may reflect economic pressures, caregiving responsibilities, or unstable living conditions rather than disengagement, as school absenteeism is widely understood to arise from multiple interacting factors, including family context, emotional distress, and environmental constraints rather than a single behavioral cause [38]. Hygiene or meal-participation patterns may similarly arise from supply or financial constraints. Interpreting such indicators without contextual understanding risks misrepresenting the underlying drivers of student behavior, particularly in vulnerable settings; accordingly, alerts should be treated as provisional signals rather than definitive classifications to avoid misclassification and stigmatization. This approach aligns with evidence that effective responses to student risk signals require functional, context-sensitive assessment [38]. Providing transparent and reviewable AI outputs, such as the indicators or assumptions behind each alert, can further support this process and reduce the risk of opaque or misleading inferences.

Trust cannot be programmed into a system; it has to be built through relationships. One promising approach is community data stewardship, where teachers, parents, and health workers share responsibility for deciding how data are used and interpreted [7]. This shared model of decision-making makes AI more accountable to the people it affects. It aligns with WHO's idea of "relational governance," where technology decisions reflect both technical knowledge and social context [4, 32]. Embedding these principles into everyday workflows, such as transparent flagging criteria, routine community review, and regular communication about what the system does and does not monitor, helps ensure that AI strengthens rather than undermines trust.

Technically, federated learning can help achieve privacy while maintaining the benefits of shared learning. However, privacy protection must extend beyond the choice of algorithm. A school-level AI system should incorporate privacy-by-design practices such as local data storage, limited access roles, and routine audit logs. AI tools should provide clear, reviewable outputs so that school staff can understand the basis of each alert. Even with these safeguards, AI-generated outputs must remain advisory: human review is the final step before any action is taken. Children's data require heightened vigilance for autonomy, privacy, and informed consent.

5 Conclusions

The goal for LMICs is not to import advanced systems but to nurture wise ones, with practical school-level AI designed to remain simple, explainable, able to run offline, and built to work with the small and imperfect datasets that schools already collect, while fitting into existing routines and producing alerts that are easy for staff to understand and review.

A locally intelligent school health ecosystem, ethical, data-informed, and community-led, can redefine prevention from the ground up. To support this, schools and ministries can adopt a few basic policy steps: (1) setting minimum data standards; (2) establishing a clear process for how alerts are reviewed by staff; and (3) involving teachers and families in decisions about data use. These structures help ensure the tools remain trustworthy, proportional, and grounded in local needs.

However, several limitations should be acknowledged, including the irregular and sometimes non-longitudinal nature of routine school data, the reliance on proxy indicators of student well-being, broader feasibility constraints related to tool availability and local technical capacity, and the need to track individual-level changes over time for meaningful early detection, which introduces inherent privacy and data governance challenges.

In resource-limited settings, the value of AI lies less in computational sophistication and more in supporting timely understanding and context-appropriate decision-making. When integrated into routine school processes, such systems can help shift prevention from reactive responses to more consistent, day-to-day practice.

Abbreviations

AI	Artificial intelligence
Explainable AI	Explainable artificial intelligence
LMICs	Low- and middle-income countries
WHO	World Health Organization

Glossary

Adolescent health	The physical, mental, and social well-being of individuals typically aged 10.
Explainable artificial intelligence (explainable AI)	AI methods designed to produce outputs that are transparent and understandable to non-specialists, allowing users to see how and why patterns or alerts are generated.
Early warning signals	Subtle, early changes in routinely collected indicators, such as attendance or meal participation, that may suggest emerging health or well-being concerns.
Federated learning	A privacy-preserving approach to model training in which data remain stored locally while only aggregated model updates are shared across sites.
Routine school data	Information regularly collected by schools during normal operations, including attendance records, basic health checks, hygiene monitoring, and participation in school meal programmes.
Small-data AI	Analytical approaches designed to work with limited, imperfect, and locally generated datasets, emphasizing simplicity, adaptability, and interpretability rather than scale.

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