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Machine Learning and Student Engagement: The Role of Early Warning Systems in School Dropout Prevention

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Abstract: Student engagement, conceptualized as a multidimensional metaconstruct encompassing emotional, cognitive, and behavioral components, is closely linked to dropout risk, academic success, and broader developmental outcomes. Shaped by family, school, peer, and community factors, it serves as a key indicator within prevention efforts. In the Italian context, the growing availability of educational data produced by the digitalization of school systems supports the adoption of Early Warning Systems (EWS) as promising tools for the timely identification of at-risk students. Based on data analytics and machine learning, these tools provide proactive support for monitoring and guiding timely interventions. This contribution provides a research overview on the potential of AI-supported Early Warning Systems in education, examining how these tools can identify patterns of participation, disengagement, and everyday school dynamics. The aim is to explore whether combining algorithmic indicators with contextual qualitative information, professional judgment (human-in-the-loop), and adequate teacher training can enhance the accuracy and usefulness of predictions, while promoting more informed, inclusive, and networked educational practices. Such an approach may enable schools to leverage AI not merely as a monitoring tool, but as a catalyst for targeted actions that support student participation, agency, and long-term well-being.

Keywords: Student Engagement, Early Warning System, School-based intervention, Early School Leaving.

1. Introduction

Student engagement serves as a malleable determinant of educational success, conceptualized as a multidimensional metaconstruct encompassing emotional, cognitive, and behavioral domains (Finn & Zimmer, 2012; Fredricks et al., 2019). Early school leaving (ESL) remains a critical systemic issue in Italy, with significant long-term implications for students' well-being. The Italian educational landscape is marked by profound territorial disparities in learning opportunities, as evidenced by recent data. A distinct fracture emerges between Northern and Southern regions regarding "implicit school dropout" versus “academic excellence” (INVALSI, 2025).

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Pronounced territorial disparities characterize the Italian context, contrasting Northern academic excellence with Southern regions where implicit dropout risk exceeds 25-30%. This dichotomy underscores the urgency for targeted interventions tailored to specific socio-economic and environmental variabilities.

The European Council's strategic framework (2021-2030) sets the ambitious target of reducing early school leaving to below 9% by 2030, prioritising quality, equity, inclusion and success for all. This dual objective aims to decouple educational achievement from socio-economic status, particularly protecting students with disabilities or from migrant backgrounds. Contrary to the perception of early school leaving as a sudden event, it is the culmination of a long process of disengagement (Finn & Zimmer, 2012).

As noted by Eurydice and the Italian Authority for Children and Adolescents (2022), addressing this invisible process requires structural early warning systems that recognise school as a key place for prevention and for making students feel "seen" by both their peers and their educators. A paradigm shift from reactive observation to proactive identification is required, necessitating substantial investment in Continuous Professional Development (CPD) to translate algorithmic data into pedagogical action. While digitalization enables AI-driven EWS to detect complex, non-linear disengagement patterns, their deployment should prioritize "Equity First" and "Human-in-the-loop" frameworks, ensuring that insights augment professional judgment (Molenaar, 2022). Accordingly, this review has examined the potential of AI-enhanced Early Warning Systems to support student engagement and prevent early school leaving, with particular attention to implementation considerations within the Italian educational context.

2. Theoretical Framework

Student engagement is widely recognised not as a static characteristic, but as a dynamic and multidimensional metaconstruct that evolves significantly from childhood to adolescence (Archambault et al., 2019). The variables underlying this model link the fields of education and psychology. From a psychological perspective, the framework is based on concepts such as self-efficacy, motivation and emotional regulation, which stimulate students' internal commitment to learning. According to this concept, "motivated commitment" and "self-efficacy beliefs" are highlighted as central factors that enable students to persevere despite difficulties. From a pedagogical perspective, the model integrates the principles of data-driven education, in which performance is a function of the achievement of specific competencies (Namoun & Alshanqiti, 2021). Secondly, involvement is defined as a "malleable state", meaning that it is highly sensitive to contextual factors and susceptible to change through targeted interventions in the school and family environment (Fredricks et al., 2019).

2.1. The Invisible Process

Engagement is frequently reduced to its visible markers, yet its core operates as an invisible process of internal regulation. This dimension involves metacognitive strategies and emotional responses that are decisive for academic success but not immediately observable. For instance, the internal processing of "academic emotions", such as anxiety or satisfaction, impacts a student's ability to engage with learning materials (Namoun & Alshanqiti, 2021). This invisible aspect includes the cognitive effort involved in self-regulation, deliberation, and resoluteness, which precedes the observable action of studying.

In line with the fundamental multidimensional models outlined above, engagement can be divided into three distinct but interrelated dimensions (Fredricks et al., 2019). First, the behavioural engagement, this observable dimension manifests itself through participation, conduct, and involvement in academic and extracurricular activities. It includes positive behaviours such as compliance with school rules and active participation in educational activities, along with the absence of disruptive behaviours (Archambault et al., 2019; Fredricks et al., 2019). In online contexts, this aspect is monitored through records of interactions with learning management systems, as will be explained below (Namoun & Alshanqiti, 2021). The second aspect is emotional involvement. This dimension includes emotional reactions towards school, teachers and classmates, including interest, boredom, happiness and anxiety. These can be summarised as the student's sense of belonging and identification with the school. The literature analyses in particular the role of "emotional reactions" and the expression of satisfaction as key components of this dimension. The final dimension, cognitive engagement, concerns the student's psychological investment in learning, characterised by the use of deep processing strategies, flexibility in problem solving and self-regulation. It includes metacomprehension and the willingness to exert the effort necessary to understand complex ideas (Fredricks et al., 2019).

2.2. Influencing Factors

Student engagement is not an isolated phenomenon, but is shaped by a complex ecosystem of influential factors, confirming its status as a context-dependent variable. Engagement is a developmental process that begins before formal education and continues into early adulthood (Fredricks et al., 2019). It is highly sensitive to the learning environment, as is already well known; therefore, effective prevention and intervention strategies can be implemented from childhood to adolescence to promote engagement and prevent school dropout (Archambault et al., 2019). The first of these contributing factors is therefore collaboration between the family and the school: the family microsystem plays a fundamental role. Research indicates that positive collaboration between the school and the family, characterised by mutual respect and dialogue, is very important for students' well-being (Pieri, 2018). Family support is therefore a crucial resource which, together with the school environment, promotes the development of the skills necessary for school adaptation (Archambault et al. 2019).

Other relevant and determining factors are pedagogical and technological: the quality of the learning environment, including the quality of teaching and course design (Namoun & Alshanqiti, 2021). In blended learning contexts, cooperative learning methodologies and personalised feedback are essential for promoting metacognitive skills. Furthermore, the integration of ICT (Information and Communication Technology) facilitates communication but requires careful management and observation to support engagement without causing unpleasant situations (Pieri, 2018).

3. Data Analytics and Early Warning Systems (EWS)

The emergence of data-driven educational technologies has positioned Early Warning Systems as pivotal tools in addressing the multifaceted challenge of student disengagement. These systems leverage the increasing digitalization of educational environments to transform vast amounts of administrative, behavioral, and academic data into actionable insights for educators.

Nevertheless, the efficacy of EWS extends beyond mere technological implementation; it requires a nuanced understanding of the data types employed, the algorithmic methodologies applied, and the institutional contexts within which these systems operate.

3.1. Data Types and Predictive Indicators

Contemporary EWS architectures integrate multiple data dimensions to construct comprehensive risk profiles. Academic performance metrics—including grades, test scores, and course completion rates—constitute the foundational layer of predictive models (Liz-Domínguez et al., 2019). However, research increasingly demonstrates that behavioral indicators provide equally critical signals of disengagement. Attendance patterns, disciplinary incidents, and participation in extracurricular activities have proven to be particularly robust predictors of dropout risk (Mac Iver & Mac Iver, 2009; Balfanz et al., 2007). In digital learning environments, additional behavioral data streams emerge through learning management systems, capturing patterns of resource access, assignment submission timeliness, and online participation frequency (Namoun & Alshanqiti, 2021).

Recent implementations have also incorporated socio-emotional indicators derived from surveys and self-report instruments, recognizing that psychological factors such as self-efficacy, sense of belonging, and academic motivation significantly mediate engagement trajectories (Pardo et al., 2019). This multimodal data integration aligns with the multidimensional conceptualization of student engagement, acknowledging that cognitive, behavioral, and affective dimensions interact dynamically to shape educational outcomes.

3.2. Machine Learning Approaches and Algorithmic Architectures

The analytical foundation of contemporary EWS has evolved considerably beyond traditional statistical regression models. While early implementations employed logistic regression to identify at-risk students (Balfanz et al., 2007), the complexity of educational processes necessitates more sophisticated approaches capable of capturing non-linear relationships and higher-order interactions among variables. Systematic reviews of predictive modeling in education reveal that ensemble methods—particularly Random Forest and Gradient Boosting algorithms such as XGBoost—consistently demonstrate superior predictive accuracy compared to simpler techniques (Rastrollo-Guerrero et al., 2020; Namoun & Alshanqiti, 2021). Random Forest models, which aggregate predictions from multiple decision trees trained on bootstrapped samples, excel at handling high-dimensional data and identifying complex interaction effects without extensive feature engineering (Breiman, 2001). XGBoost extends this framework through gradient boosting, sequentially constructing trees that correct errors of previous iterations while incorporating regularization to prevent overfitting (Chen & Guestrin, 2016). In educational contexts, these algorithms have achieved prediction accuracies exceeding 85% for dropout risk classification, substantially outperforming traditional methods (Hlioui et al., 2020).

Deep learning architectures, particularly RNNs and LSTMs, offer robust capabilities for modeling temporal dynamics and predicting longitudinal disengagement patterns (Waheed et al., 2019). However, their deployment is often constrained by high computational demands and the necessity for extensive training datasets, potentially limiting applicability in resource-scarce educational contexts.

3.3. Implementation Contexts and Effectiveness Evidence

Empirical evidence regarding EWS effectiveness reveals a nuanced landscape. In higher education contexts, several large-scale implementations have documented promising outcomes. However, critical examination reveals important caveats. A recent qualitative study examining students' experiences with AI-powered educational tools, including an EWS, highlighted concerns regarding the transparency of algorithmic decision-making and the potential for systems to generate anxiety rather than support when predictions are poorly communicated (Rodríguez et al., 2024). Students reported feeling "labeled" by risk classifications and expressed uncertainty about how to productively respond to system-generated alerts.

In K-12 contexts, particularly within the Italian educational system, EWS implementation remains nascent. A recent master's thesis examining the feasibility of EWS deployment in Italian K-12 education identified significant infrastructural and cultural barriers (Marani Tassinari & Mylonopoulou, 2024). These include fragmented data systems across schools, limited technological infrastructure in certain regions (particularly those already experiencing high implicit dropout rates), and concerns regarding privacy protections under GDPR regulations. The study emphasized that successful implementation would require not merely technological deployment but substantial investment in teacher professional development and clear protocols for translating algorithmic outputs into pedagogical action.

3.4. Ethical Considerations and Algorithmic Equity

The deployment of algorithmic decision-making systems in education raises profound ethical questions that extend beyond technical accuracy metrics. Holstein and Doroudi (2021) advocate for an "Equity First" framework, warning that models trained on historical data reflecting structural disadvantages risk perpetuating inequities and creating self-fulfilling prophecies for marginalized students. While technical mitigations—such as algorithmic auditing and fairness constraints—are necessary (Baker & Hawn, 2021), they prove insufficient without participatory design processes that engage stakeholders in defining fairness beyond mere statistical parity. Furthermore, the ethical deployment of EWS requires robust privacy governance regarding data access and informed consent (Slade & Prinsloo, 2013). In the European context, GDPR regulations on automated decision-making impose critical requirements for transparency and contestability, functioning as essential safeguards against algorithmic overreach while shaping the boundaries of system implementation.

4. Toward Hybrid Intelligence: Integrating Human Expertise and Algorithmic Predictions

The integration of AI-enhanced EWS extends beyond technical implementation, fundamentally reconceptualizing the intersection of data, professional expertise, and pedagogy. Reviewed evidence underscores that while algorithms may achieve high statistical accuracy, their actual educational utility is strictly contingent upon educators' ability to contextualize predictions and translate them into meaningful interventions.

This section examines emerging frameworks for hybrid intelligence approaches that position EWS not as autonomous decision-making systems but as augmentative tools that enhance rather than replace human judgment.

4.1. The Human-in-the-Loop Paradigm

The human-in-the-loop (HITL) approach recognizes that effective educational AI systems require ongoing human oversight, interpretation, and decision-making at critical junctures. Molenaar (2022) articulates this framework as "hybrid human-AI learning technologies", emphasizing that the complementary strengths of human educators and algorithmic systems can create outcomes superior to either operating independently. Teachers possess contextual knowledge—awareness of family circumstances, recent life events, peer dynamics, and cultural factors—that algorithms cannot access through quantitative data alone. Conversely, algorithms excel at processing large volumes of data to identify subtle patterns that might escape human attention amid the demands of daily classroom management.

Implementing HITL approaches requires careful attention to several design principles. First, transparency in algorithmic reasoning proves essential. Systems must provide educators not merely with risk classifications but with explanations of which factors contributed most significantly to predictions. Explainable AI (XAI) techniques, such as SHAP (SHapley Additive exPlanations) values or feature importance visualizations, can make algorithmic reasoning comprehensible to non-technical users (Molnar, 2025). Second, actionability must be prioritized: alerts should be accompanied by suggested intervention strategies tailored to the specific risk factors identified. Third, systems should incorporate mechanisms for teacher override, allowing educators to document situations where algorithmic predictions do not align with their professional judgment and contextual knowledge (Holstein & Doroudi, 2021).

4.2. Integrating Quantitative Indicators with Qualitative Insights

A comprehensive approach to EWS implementation must bridge the quantitative-qualitative divide that has historically characterized educational research and practice. While algorithmic models process numerical indicators—attendance rates, grade point averages, disciplinary incidents—these metrics capture only partial dimensions of student experience. The multidimensional model of engagement discussed in Section 2 highlights the necessity of attending to cognitive, emotional, and behavioral dimensions simultaneously, many of which resist straightforward quantification. Effective hybrid systems integrate structured qualitative mechanisms—such as teacher observation protocols (Fredricks et al., 2019) and student self-reports—to capture behavioral, cognitive, and emotional dimensions often missed by quantitative proxies. Natural language processing techniques can identify themes and sentiment in open-ended responses, while still preserving opportunities for educators to read individual student narratives when algorithmic alerts warrant closer attention.

4.3. Professional Development and AI Literacy for Educators

The effective integration of EWS hinges on targeted professional development fostering "AI literacy" rather than technical expertise. As defined by Long and Magerko (2020), this competence entails a foundational understanding of algorithmic capabilities and limitations, enabling the strategic incorporation of AI insights into pedagogical decision-making. Professional development should address several key competencies: a conceptual grasp of the probabilistic nature of predictive models to foster critical skepticism; interpretative skills to synthesize algorithmic outputs with professional observation; and ethical awareness regarding bias, privacy, and the prevention of stigmatization (Di Martino, 2025). Professional development should transcend technical training to cultivate a broader data-driven culture. By acquiring competence in integrating heterogeneous data sources—combining algorithmic insights with qualitative observation—educators are empowered to provide holistic support to the entire student population, extending beyond solely those identified by warning systems.

4.4. Systemic Considerations for the Italian Context

The implementation of hybrid intelligence approaches within Italian schools must navigate several context-specific challenges. As noted in Section 1, the Italian educational landscape exhibits profound territorial disparities, with regions in the South experiencing significantly higher implicit dropout rates alongside more limited technological infrastructure (INVALSI, 2025). This reality demands differentiated implementation strategies that acknowledge varying levels of digital readiness across schools. Furthermore, the fragmented nature of Italian school data systems presents obstacles to comprehensive EWS deployment. Unlike centralized systems in some countries, Italian schools often maintain data across multiple disconnected platforms, complicating efforts to aggregate information necessary for predictive modeling (Marani Tassinari & Mylonopoulou, 2024). A phased approach may prove most feasible: beginning with pilot implementations in schools with stronger technological foundations, gathering evidence of effectiveness, and subsequently expanding to additional contexts with lessons learned and refined protocols. The Italian normative landscape, governed by GDPR, imposes strict requirements for consent and automated decision-making (Slade & Prinsloo, 2013). Far from being impediments, these function as ethical design constraints ensuring transparency and dignity. Moreover, the inherent congruence between the Italian tradition of relational pedagogy and hybrid intelligence models resists reductive algorithmic scoring, positioning data as a complementary asset within a holistic educational framework.

5. From Alert to Preventive Action

The ultimate utility of EWS transcends predictive accuracy, residing fundamentally in the capacity to catalyze timely intervention. However, a persistent implementation gap remains, severing the link between algorithmic identification and the delivery of meaningful support addressing the root causes of disengagement. This section examines frameworks and strategies for translating EWS alerts into concrete pedagogical action, emphasizing that prevention requires coordinated, multi-level responses that engage not only individual students but also their broader educational ecosystems.

5.1. Multi-Tiered Systems of Support (MTSS)

Multi-Tiered Systems of Support (MTSS) provide a structured framework for organizing interventions based on student need intensity. Originally developed within Response to Intervention (RTI) models, MTSS frameworks conceptualize support across three tiers: universal interventions benefiting all students (Tier 1), targeted supports for students showing early warning signs (Tier 2), and intensive individualized interventions for students at highest risk (Tier 3) (Freeman et al., 2017).

EWS integration with MTSS creates natural alignment: algorithmic risk classifications can guide tier placement, while ongoing monitoring tracks student response to intervention, informing decisions about intensification or de-escalation of support. At Tier 1, schools focus on creating engaging learning environments for all students through evidence-based instructional practices, positive school climate initiatives, and clear behavioral expectations. These universal supports establish the foundation upon which targeted interventions build. At Tier 2, students flagged by EWS receive supplementary interventions such as small-group tutoring, check-in/check-out behavioral support, or social-emotional learning groups. These interventions are time-limited, regularly monitored, and adjusted based on student progress. At Tier 3, students with persistent difficulties despite Tier 2 support receive individualized, intensive interventions developed through comprehensive assessment and often involving specialized personnel such as school psychologists, social workers, or special education teachers (Fredricks et al., 2019).

5.2. Intervention Strategies Aligned with Engagement Dimensions

Effective intervention requires matching strategies to the specific engagement dimensions showing decline. The multidimensional framework discussed in Section 2 provides guidance for intervention selection. Addressing behavioral disengagement necessitates pragmatic measures such as mentoring, structured support, and incentive systems (Archambault et al., 2019). Countering emotional withdrawal requires relationship-centered approaches—including counseling and social-emotional learning—to restore a sense of belonging (Fredricks et al., 2019). Finally, cognitive disengagement demands instructional interventions that cultivate metacognition and intrinsic motivation through strategy instruction and curricular relevance.

5.3. Family and Community Involvement

Student engagement cannot be understood or addressed solely within school walls. As discussed in Section 2, family factors significantly influence engagement trajectories. Effective dropout prevention requires collaborative partnerships between schools and families characterized by mutual respect, regular communication, and shared responsibility for student success (Pieri, 2018). EWS enable proactive family engagement via data-informed dialogue, provided communication is framed as a non-stigmatizing collaborative partnership (Christenson & Reschly, 2010). Concurrently, external partnerships expand institutional capacity; notably, community schools models serve as hubs for coordinating comprehensive services to address the multifaceted determinants of disengagement (Epstein & Sheldon, 2016).

5.4. Monitoring, Feedback Loops, and Continuous Improvement

The true power of integrating EWS with intervention systems lies in creating continuous feedback loops that enable ongoing refinement. Regular progress monitoring—whether through weekly check-ins, bi-weekly assessments, or monthly reviews—allows educators to evaluate whether interventions are producing desired effects. When students show positive response, supports can be gradually reduced; when progress stagnates, interventions require intensification or modification.

At the system level, schools should analyze aggregate data to identify patterns in which students are identified, which interventions prove most effective, and where gaps in support exist. This organizational learning enables continuous improvement of both the EWS itself and the intervention ecosystem surrounding it. Predictive models can be recalibrated based on outcome data, new features can be incorporated as their predictive value becomes evident, and resource allocation can shift toward interventions demonstrating greatest impact (Pardo et al., 2019).

6. Conclusions

The integration of AI-enhanced Early Warning Systems into education represents not merely a technological innovation but an opportunity for systemic transformation. When implemented thoughtfully—with attention to hybrid intelligence, ethical considerations, and comprehensive intervention systems—these tools can shift educational practice from reactive crisis management toward proactive, preventive support. The goal extends beyond reducing dropout statistics to fundamentally reconceptualizing how schools identify, understand, and respond to student needs. In the Italian context, marked by pronounced regional disparities yet rich pedagogical traditions emphasizing relationship and holistic development, EWS implementation offers possibilities for leveraging data and algorithms in service of more equitable, inclusive, and genuinely supportive educational environments. The challenge lies not in whether to adopt these technologies but in how to do so in ways that honor student dignity, amplify teacher expertise, and ultimately serve the flourishing of all learners.

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