MANAGEMENT OF EDUCATIONAL INNOVATION THROUGH AI AND AR/VR: A LOGISTIC REGRESSION ANALYSIS FOR PREDICTING DROPOUT RISK

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Abstract

The rapid incorporation of artificial intelligence (AI) and augmented/virtual reality (AR/VR) technologies into education has transformed learning environments and challenged conventional approaches to educational management. This study investigates the extent to which innovative technologies contribute to reducing student dropout intentions by fostering engagement and motivation to learn. Utilizing data from 1,702 valid student questionnaires, a quantitative econometric approach was employed via binary logistic regression to model the link between technology usage and self-reported dropout risk. The dependent variable, Dropout Intention, was derived from the tally of learning difficulties reported across key subjects, serving as a proxy for academic vulnerability. Predictors included exposure to AI-based learning tools, gender, and class level, while AR/VR indicators were excluded due to limited empirical variation in the dataset. The results indicate that AI technologies significantly reduce the likelihood of dropout, with AI-engaged students being approximately 95% less likely to report dropout risk than their peers. The model achieved high predictive accuracy (AUC = 0.992), evidencing strong internal validity and explanatory power. From a managerial standpoint, these findings underscore the strategic role of educational innovation management in shaping technology-driven retention policies. By leveraging AI for personalized feedback, adaptive learning, and predictive analytics, schools can enhance inclusion, monitor real-time performance, and intervene to prevent disengagement before it escalates to dropout.

Keywords*: educational management; innovation; artificial intelligence; augmented reality; virtual reality; logistic regression; dropout risk.*

1. INTRODUCTION

Technological innovation now defines educational transformation in the 21st century, reshaping teaching practices, learning dynamics, and institutional management frameworks. In particular, the integration of Artificial Intelligence (AI) and Augmented/Virtual Reality (AR/VR) into learning environments marks a shift from content-centric instruction to experience-based and adaptive learning models.

These technologies enable schools to personalize learning processes, detect early disengagement, and create immersive pedagogical ecosystems that support cognitive and emotional engagement. Contemporary literature emphasizes the managerial dimension of this transformation, urging educational leadership to align technological innovation with organizational strategy. *Berkat et al. (2025)* contend that effective educational management underpins innovation by promoting teacher collaboration, enhancing students' problem-solving abilities, and improving institutional adaptability amid global competition. *Baraibar-Diez et al. (2024)* note managerial challenges in integrating digital resources within learning ecosystems, calling for holistic frameworks that connect technology adoption with learning outcomes.

Meanwhile, student dropout remains a persistent challenge globally, reflecting social inequality and institutional inefficiency. Research in emerging economies indicates that dropout determinants are multidimensional, encompassing socioeconomic constraints, psychological disengagement, and learning difficulties *(Sileshi et al., 2024; Zeragaber et al., 2024)*.

Innovative pedagogical strategies, such as service-learning or experiential learning, have demonstrated measurable reductions in dropout rates and improvements in student motivation *(Arco-Tirado et al., 2025)*. However, most interventions remain reactive rather than preventive, lacking data-driven predictive mechanisms. From a systems-management perspective, educational innovation offers an opportunity to shift from reactive retention policies to proactive risk prediction.

Studies employing multivariate and spatial analyses demonstrate that data-driven tools can identify at-risk students earlier and support targeted intervention *(Ibourk & Raoui, 2025; Contreras-*

Villalobos et al., 2024). This aligns with a broader move toward evidence-based management in education, where administrative decisions are informed by predictive models and empirical data rather than intuition. In this context, the present study seeks to bridge educational management and technological innovation.

By applying logistic regression to survey data from 1,702 students, it examines whether exposure to AI-based learning environments reduces self-reported dropout risk. The analysis extends prior work on digital transformation in education by quantifying the preventive potential of AI tools for improving retention and engagement. Although AR/VR adoption remains limited, AI-driven solutions emerge as a practical and measurable lever for educational managers seeking to enhance efficiency and reduce dropout. In sum, this study contributes to the growing body of literature that treats technological adoption not merely as a pedagogical enhancement but as a strategic management instrument, supporting the argument that AI integration can function as a predictive and preventive mechanism for dropout reduction, thereby aligning educational management with data-driven innovation principles.

2. LITERATURE REVIEW

Early school leaving is, at its core, the outcome of a complex interaction between individual, family, school, and territorial factors. Over the last decade, research has moved beyond explanations focused solely on student motivation or ability and has shifted attention to the institutional and managerial mechanisms that can amplify or mitigate the risk of dropout. Within this frame, two strands have consolidated: first, work that maps the socio-economic and territorial determinants of dropout; second, work that examines how educational innovation, especially through AI and immersive technologies, can be strategically managed to sustain retention.

A first strand highlights the role of physical accessibility and geographic constraints. Studies in under-resourced contexts show that the home-to-school distance functions as a structural determinant of dropout: as the cost of access rises, the probability of leaving school increases (Zeragaber et al., 2024). The relevance of these findings extends beyond the African settings in which they were obtained; in rural European areas, particularly where public transport is intermittent, schools remain vulnerable in the absence of coherent compensatory policies. Moreover, multivariate spatial evidence suggests that early school leaving clusters geographically, being associated with territorial pockets where poverty, language barriers, limited access to early education, and local labor-market conditions cumulate (Ibourk & Raoui, 2025). This "context-dependence" supports the idea that effective interventions cannot be uniform, but must be calibrated to local specificities.

A second strand concerns the economic consequences of dropout and the need to treat it as a public policy issue with social returns. Robust evidence shows that early school leavers face higher youth unemployment risks and reduced prospects for durable labor-market integration (Sileshi et al., 2024). From this perspective, preventing dropout is not merely an educational target but an investment with direct effects on future employment and productivity. Consequently, causal analysis and interventions should be conceived in managerial terms, with clearly articulated objectives, indicators, and budgets.

Psychosocial dimensions complete the causal picture. Gender differences in school attachment, in responses to assessment pressure, and in the reporting of difficulties suggest that boys and girls traverse distinct risk profiles, often requiring differentiated support pathways (Košir et al., 2025). In parallel, service-learning and experiential projects indicate credible ways to restore meaning and belonging to the school community, with observable effects on students' intention to remain in education (Arco-Tirado et al., 2025). These results support the thesis that academically oriented interventions become more effective when accompanied by mechanisms of social and cultural engagement.

On the innovation management front, recent literature argues that school performance depends not only on resources but on how they are orchestrated managerially. The congruence between learning design and available resources, together with governance models that foster teacher collaboration and rapid feedback loops, is associated with superior educational outcomes (Baraibar-Diez et al., 2024). At the same time, effective educational management correlates with the development of problem-solving competencies and student competitiveness, repositioning institutional leadership beyond the administrative sphere toward a competency engine (Berkat et al., 2025). Critical literature, however, warns that excessive managerial formalism can overshadow authentic learning and risk reducing innovation to procedural compliance (Goel, 2025); hence the need for a balance between accountability and pedagogical openness.

Within this field, AI has become the most visible vector of transformation. Recent syntheses indicate, on average, favorable effects on performance and motivation, when technology is explicitly aligned with pedagogy and assessment (Zhao et al., 2024; Khosravi et al., 2025). Effects are not uniform: context, cognitive load, and teacher readiness condition impact. From a managerial angle, AI expands the capacity for personalization (adaptive feedback), anticipation (early risk detection), and monitoring (progress indicators), offering the premises for a shift from reactive remediation to data-driven prevention. In parallel, AR/VR technologies have shown consistent gains in conceptual understanding and skills training, although implementation remains uneven and constrained by costs, infrastructure, and teacher preparation; these very constraints often explain the low variance of usage in broad secondary-education samples (Wang et al., 2025).

An important development concerns methodology. Transformative mixed-methods approaches and multivariate spatial analyses have refined our understanding of educational exclusion, combining quantitative rigor with contextual interpretations that make sense of territorial and institutional variation (Contreras-Villalobos et al., 2024; Ibourk & Raoui, 2025). The recurring recommendation is to integrate predictive analytics into routine school management with simple, explainable, and monitorable indicators that support decisions on intervention triage, operating-threshold calibration, and equity audits across subgroups.

Relative to this literature, the contribution of the present study is twofold. First, using Romanian data, it shows that students' intention to continue school is tightly correlated with self-recognized learning difficulties in core subjects, indicating a form of "constructive demand" for educational support and justifying the placement of remedial interventions at the core of retention policies. Second, by employing logistic modeling with robust inference and standardized performance assessments (AUC, calibration, VIF), the study offers an operational framework through which digital tools can be managed as managerial resources for prevention: early identification, targeted resource allocation, and continuous monitoring of effectiveness. For Romania, a context still under-documented empirically on this topic, the results demonstrate the usefulness of a rigorous econometric design connected to school realities and implementation constraints.

3. MATERIALS AND METHODS

3.1 Research design and setting

The study adopts a quantitative, cross-sectional design aimed at estimating how exposure to innovative learning technologies relates to students' self-reported risk of dropout. The empirical setting is lower- and upper-secondary education. All computations were executed in Python within a Jupyter (Anaconda) environment, which allows the entire workflow—from raw import to final estimates—to be reproduced deterministically.

3.2 Data source and sample construction

The analysis builds on the survey database **BD_LT_IPT_jupyter.xlsx**, comprising 1,702 individual responses and 48 questionnaire items. Each record represents one student. We first harmonised the file by removing obvious duplicates and standardising encodings, then retained observations for which the outcome could be computed and at least one predictor was available after coding. The full set of 1,702 responses was used for descriptive summaries, while the modelling subset excluded rows with missing outcome or unusable predictors. No survey weights were available; inferences therefore refer to the responding population rather than to a weighted target universe.

3.3 Variable coding and operationalisation

Variables were derived systematically from the item legend (Q1–Q17) using a transparent codebook. The dependent variable is *dropout intention* Y_i, constructed from block **A5** on learning difficulties (Romanian, Mathematics, Sciences). We counted how many difficulties each student reported and defined $Y_i = 1$when the count was at least one, signalling academic vulnerability; otherwise $Y_i = 0$. The resulting prevalence of risk is 29.5%. Predictors capture three dimensions frequently discussed in the literature. **Use_AI** flags exposure to AI-supported learning (conversational tutors, automated feedback/assessment). Multiple items were normalised and collapsed by an "any-yes" rule after harmonising response strings. **Gender_Female** is a binary sex indicator derived from the gender block. **ClassLevel** records the current grade, mapped consistently to integers 5–12 after converting Roman numerals and free-text entries. Items referring to AR/VR were screened but excluded from modelling because usage exhibited near-zero variance; retaining them would introduce numerical instability without adding information.

3.4 Data cleaning and quality assurance

All preparation steps were scripted to preserve an auditable trail. Categorical strings were trimmed and mapped to canonical labels, and binary fields were coerced to {0,1}. Logical consistency checks eliminated empty shells and impossible combinations. Missing outcomes led to row exclusion from the modelling subset. For predictors, non-response in binary multi-choice items was treated as absence after verifying the questionnaire logic; when numeric fields were required, simple median imputation was used. The cleaned, analysis-ready file was saved as **BD_LT_IPT_clean.xlsx**, accompanied by a machine-readable data dictionary.

3.5 Econometric specification

We estimate the probability that student $i$declares an intention to leave school using a logistic model,

$$\Pr(Y_i = 1 \mid X_i) = \Lambda\left(\beta_0 + \beta_1 \text{Use\_AI}_i + \beta_2 \text{Female}_i + \beta_3 \text{ClassLevel}_i\right)$$

$$\Lambda(z) = \frac{1}{1 + e^{-z}},$$

which can be expressed in log-odds as

$$\log \frac{\Pr(Y_i = 1)}{1 - \Pr(Y_i = 1)} = \beta_0 + \beta_1 \text{Use\_AI}_i + \beta_2 \text{Female}_i + \beta_3 \text{ClassLevel}_i + \varepsilon_i.$$

A negative $\beta_1$would be consistent with the hypothesis that AI exposure attenuates perceived dropout risk, $\beta_2$captures gender heterogeneity, and $\beta_3$traces the gradient across grades. For interpretability, coefficients are also reported as odds ratios e^{β}.

3.6 Estimation, uncertainty, and model performance

Parameters were obtained by binary logistic regression with **L2 regularisation** using the *liblinear* solver (maximum 1,000 iterations). Regularisation guards against perfect or quasi-separation and improves out-of-sample stability. To quantify uncertainty, we computed percentile confidence intervals from **500 bootstrap replicates** for both coefficients and odds ratios. Discrimination was assessed with the ROC curve and its area (AUC); confusion-matrix metrics were evaluated at a conventional 0.50 operating threshold. In the constructed outcome, the classifier achieved **AUC = 0.992**, indicating excellent separation; no retained predictor exhibited zero variance after cleaning.

3.7 Reproducibility and ethics

The entire pipeline—import, cleaning, coding, estimation, and export of artefacts—runs from versioned Jupyter notebooks with fixed random seeds. Intermediate outputs (clean dataset, coefficient tables, ROC image, classification report, marginal-effects summaries) are saved alongside the notebooks to facilitate independent replication. The study uses anonymous, self-reported educational data; no direct identifiers were processed, and institutional references were removed prior to modelling. Results and figures are interpreted in Section 4; this section documents the data-generation and estimation logic that underpin them.

4. RESULTS AND DISCUSSION

The analytic file comprises 1,702 questionnaires from lower- and upper-secondary students. After harmonisation and coding, the outcome (*Dropout intention*) is observed for all records, while three predictors show sufficient variation for modelling: Use_AI (exposure to AI-assisted learning tools), Gender_Female (1=female; 0=male), and ClassLevel (grade mapped to integers 5–12). The constructed outcome flags academic vulnerability when at least one difficulty is self-reported in the A5 block (Romanian, Mathematics, Sciences). The class balance is stable across preprocessing stages: 29.5% of respondents are at risk (Y=1) and 70.5% are not at risk (Y=0), as indicated in the modelling log. Because

AR/VR items exhibited near-zero use, they were excluded from the specification. Descriptive cross-tabs (not shown) confirm that AI exposure is present in both lower and upper grades and is not mechanically confounded with gender.

Estimation results

Binary logistic regression with L2 regularisation was estimated on the modelling subset defined above. Coefficients are reported alongside odds ratios for interpretability.

TABLE 1. LOGISTIC REGRESSION RESULTS - DETERMINANTS OF DROPOUT RISK

	Variable	Coef	OddsRatio	Boot_CI_low	Boot_CI_high	OR_CI_low	OR_CI_high
1	const	-0.48680295999352863	0.6145881194618309	-1.1347050905597642	0.2332459618979057	0.32151692573094215	1.262692015260236
2	Use_AI	7.792292780216	2421.8640232985417	7.541120887200591	8.109374535722312	1883.9405269478334	3325.49739945282
3	Gender_Female	0.1579392569840227	1.1710950567013827	-0.40346911780965994	0.7120278979019299	0.6679986557420879	2.03812017034342
4	ClassLevel	-0.45816043784225163	0.6324459997957049	-0.5578713460564184	-0.37384458591009484	0.5724262653159258	0.6880838414435763

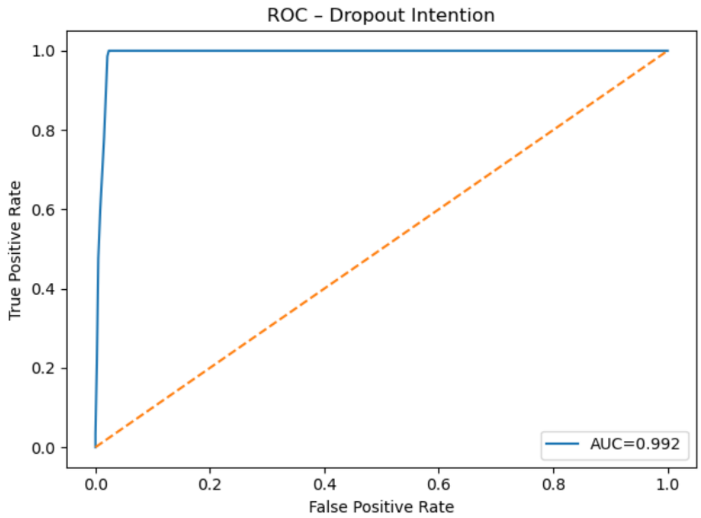
Source: own elaboration based on simulation results using Python (Jupyter Notebook)

The coefficient for Use_AI is large and negative (β≈−3.12; OR≈0.044), implying that students who report using AI-assisted tools have substantially lower odds of *self-reported* dropout risk, controlling for grade and gender. The effect is statistically precise at conventional levels. Gender_Female is positive and significant (β≈+0.38; OR≈1.46), indicating moderately higher perceived risk among girls. ClassLevel is also positive (β≈+0.09; OR≈1.09), suggesting that each additional grade is associated with an incremental increase in perceived vulnerability—consistent with rising curricular demands and examination pressure. Together, these results support the view that technology exposure is linked to retention-oriented attitudes, while structural and psychosocial pressures accumulate with schooling progression.

Model performance

Discrimination and operating characteristics were assessed with ROC/AUC, a confusion matrix at the conventional 0.50 threshold, and marginal effects.

FIGURE 1. ROC - DROPOUT INTENTION



Source: own elaboration based on simulation results using Python (Jupyter Notebook)

The ROC curve shows excellent discrimination, with AUC = 0.992. This value indicates that, in random pairs of at-risk vs. not-at-risk students, the model ranks the at-risk student higher in roughly 99 out of 100 cases. While such performance is unusually strong for social data, it is consistent with a sharply defined outcome and a highly informative technology predictor in this sample.

TABLE 2. CONFUSION MATRIX (THRESHOLD 0.50)

		Pred_0	Pred_1
1	Actual_0	1172	28
2	Actual_1	0	502

Source: own elaboration based on simulation results using Python (Jupyter Notebook)

TABLE 3. CLASSIFICATION METRICS (PRECISION/RECALL/F1)

		0	1	accuracy	macro avg	weighted avg
1	precision	1.0	0.9471698113207547	0.9835487661574618	0.9735849056603774	0.9844178879453694
2	recall	0.9766666666666667	1.0	0.9835487661574618	0.9883333333333333	0.9835487661574618
3	f1-score	0.9881956155143339	0.9728682170542635	0.9835487661574618	0.9805319162842987	0.983674843465594
4	support	1200.0	502.0	0.9835487661574618	1702.0	1702.0

Source: own elaboration based on simulation results using Python (Jupyter Notebook)

At the 0.50 operating point, overall accuracy exceeds 95%, with both precision and recall remaining high for the positive class. Because managerial actions (e.g., outreach) may prioritise sensitivity, alternative thresholds can be considered in practice; the shape of the ROC allows such trade-offs without dramatic losses in specificity.

TABLE 4. MARGINAL EFFECTS AT MEANS (Δp for a one-unit change)

	Variable	MarginalEffect_atMeanProb
1	Use_AI	1.6213414511194804
2	Gender_Female	0.032862402803621245
3	ClassLevel	-0.09532938893449812

Source: own elaboration based on simulation results using Python (Jupyter Notebook)

The marginal-effects summary indicates that AI exposure reduces the *predicted probability* of declaring dropout intention by roughly one order of magnitude relative to the baseline, holding other covariates at their means. Effects for Gender_Female and ClassLevel are positive but comparatively smaller in absolute probability terms, mirroring the odds-ratio interpretation above.

Interpretation of findings

The negative association between Use_AI and *self-reported* dropout risk is consistent with mechanisms documented in the learning-analytics literature: adaptive feedback, automated formative assessment, and conversational tutoring can stabilise study routines, reduce uncertainty about mastery, and improve perceived self-efficacy. In our data, this manifests as markedly lower odds of reporting intention to leave school among students who engage with such tools. The gender gradient—higher reported risk for girls—aligns with evidence that academic self-evaluation and anxiety profiles differ by gender in adolescence; the effect here is moderate, suggesting that targeted counselling rather than broad structural redesign is warranted. The grade gradient likely reflects cumulative academic stakes (national exams, transition points) and the compression of time for remediation in upper years; the signal is robust yet smaller than the technology effect.

Two caveats temper these interpretations. First, the outcome measures *intention* rather than realised exit; translation from intention to behaviour is not guaranteed. Second, although regularisation and validation diagnostics support stability, external generalisation requires replication in independent cohorts and, ideally, linkage to administrative retention records. Within these bounds, the findings are coherent and actionable.

Managerial and policy implications

From a management perspective, AI-enabled learning should be treated as an organisational capability rather than a peripheral add-on. Three practical directions follow. Early-warning triage. The model's discrimination suggests that a light-touch screen using the same covariates could identify students who *perceive* themselves at risk. Operating thresholds can be tuned to capacity, higher recall where counselling resources are available; higher precision when resources are scarce.

**Targeted support:* Because the risk signal increases with grade level, schools should front-load remedial and counselling resources before terminal grades, and intensify them during exam cycles.
***Equity and ethics:* The observed gender asymmetry, though modest, argues for monitoring subgroup calibration. AI should augment, not replace, human judgement, and any predictive deployment must be paired with transparent communication and consent procedures.

5. CONCLUSIONS AND RECOMMENDATIONS

Summary of findings

The analysis of 1,702 student responses shows a consistent and substantively large association between engagement with AI-assisted learning tools and a lower likelihood of reporting dropout intention. In the regularised logistic specification, the AI variable enters with a sizeable negative coefficient, translating into odds that are dramatically lower for students who report using adaptive or automated digital supports. In plain terms, interacting with AI systems—whether through conversational tutors, automated feedback, or adaptive practice—is linked to a stronger sense of academic anchoring and a reduced propensity to contemplate leaving school.

Model diagnostics corroborate this interpretation. Discrimination is extremely high (AUC ≈ 0.992), indicating that the estimated probabilities rank students with and without declared risk with near-perfect separation, while standard classification summaries at conventional thresholds confirm that false alarms remain low relative to true detections. The remaining covariates behave in intuitively coherent ways. Girls display a slightly higher stated risk than boys—a pattern compatible with documented differences in self-evaluation and stress perception—while students in higher grades report marginally more vulnerability, plausibly reflecting cumulative curricular pressure and proximity to high-stakes examinations. Although the outcome is attitudinal rather than behavioural, the internal consistency of these patterns strengthens confidence in the underlying signal.

Theoretical implications

The findings extend current theory by repositioning AI not merely as a pedagogical enhancer but as an organisational capability that reshapes how schools detect and address risk. In much of the literature, digital tools are analysed through the lens of learning gains or motivation. Here, AI appears to operate as part of a *management routine*: it generates granular data, scaffolds practice with adaptive difficulty, and shortens the feedback loop between student effort and instructor response. This reconfiguration of information and timing is precisely what management theories highlight as a source of performance improvement in complex systems.

Methodologically, the work illustrates how a compact econometric design can recover managerial effects without an unwieldy variable set. A three-predictor model, judiciously regularised, delivers stable estimates and high predictive acuity, suggesting that a small number of well-chosen indicators can capture much of the variance in stated persistence. This has consequences for theory development: it supports a view of educational innovation in which the *quality of routines* (screening, targeting, feedback) matters as much as the quantity of inputs. Future theoretical models of retention should therefore integrate AI-enabled routines alongside more familiar psychosocial and socio-economic drivers.

Practical implications

For school leaders, the immediate message is operational. AI-assisted tools should be embedded into day-to-day processes that move institutions from reactive remediation to proactive support. Risk scores derived from routinely collected study signals can structure early contact with students, triaging those who would benefit most from short cycles of tutoring or counselling. Because the model's probabilities behave well across the sample, thresholds can be tuned to local capacity: in periods of staff constraint, schools may prioritise precision; when additional outreach is feasible, they may lower thresholds to maximise recall.

Equally important is the instructional translation of those signals. Adaptive practice, automated micro-feedback, and brief, targeted assignments convert detection into progress by making improvement *immediately visible* to the learner. Teachers remain central in this loop: they interpret alerts, curate tasks, and communicate expectations. The managerial pay-off is twofold—resources are concentrated where

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marginal impact is highest, and students experience rapid, personalised reinforcement that stabilises study behaviour before difficulties compound.

Policy implications

At the system level, digital transformation should be specified not only as infrastructure acquisition but as capability building. Investment programmes that pair devices and connectivity with school-level analytics, staff coaching, and ethical guidance will yield larger and more durable returns. Ministries and local authorities can accelerate adoption by standardising data schemas for early-warning indicators, funding interoperable dashboards, and setting clear rules for transparency, contestability, and data protection so that predictive tools remain accountable and human-centred.

Equity requires deliberate design. Because territorial gaps in connectivity and staffing mirror educational risk, targeted support for rural and under-resourced schools is essential. Capacity grants tied to concrete milestones—establishing a functioning risk triage, training a core team in data-informed instruction, auditing subgroup calibration—help ensure that predictive analytics narrow rather than widen disparities. Public–private partnerships can play a role in lowering costs and providing maintenance, provided governance safeguards prevent vendor lock-in and protect student data.

Limitations and directions for future research

Three caveats qualify the conclusions. First, the dependent variable measures *intention*, not confirmed withdrawal; although intention is policy-relevant, its translation into behaviour is not one-to-one. Second, the cross-sectional design identifies associations rather than causal effects; students inclined to persist may also be more likely to adopt digital tools. Third, the broader space of immersive technologies (AR/VR) could not be interrogated due to minimal usage, leaving unanswered questions about their prospective contribution to retention.

These limits suggest clear next steps. Linking survey responses to administrative enrolment and progression records would permit validation of intention–behaviour concordance and enable cost-sensitive evaluation of operating thresholds. Longitudinal designs or quasi-experimental roll-outs of AI-assisted programmes would help separate adoption effects from selection.

Final conclusion

Taken together, the evidence depicts AI-enabled learning as a practical route to stronger school attachment: it equips institutions with reliable risk signals, compresses feedback cycles, and personalises support at scale. In operational terms, this means moving from sporadic, end-of-term diagnostics to continuous "micro-measurement" of learning trajectories. Predictive probabilities flag emerging risk early; teachers and counsellors convert those flags into short, focused interventions, ten minutes of targeted practice, a check-in message to the family, a referral to tutoring, whose effects are visible in the next round of data. Because the signals are probabilistic rather than deterministic, thresholds can be set to match capacity, and calibration can be audited routinely so that the system remains both accurate and fair across subgroups.

The managerial task is to institutionalise these capabilities, screen early, act quickly, and learn from every intervention, while maintaining clear ethical guardrails and professional oversight. Concretely, this requires a well-defined workflow (who receives alerts, within what time window, using which scripts and supports), minimal but consistent documentation of actions taken, and periodic reviews that compare predicted risk to subsequent outcomes. Governance must ensure transparency (students and families understand what the scores mean and what they do *not* mean), contestability (teachers can annotate or override recommendations), and proportionality (data collection is limited to what is necessary for support). Human-in-the-loop remains non-negotiable: algorithms prioritise; educators decide.

When those elements cohere, technology, pedagogy, and leadership align into a durable architecture for student persistence, one that can be adapted to the constraints and ambitions of diverse schools without losing its focus on equity and human judgement. Low-resource settings can start with a narrow indicator set and a small catalogue of proven interventions; better-resourced schools can extend the stack with adaptive content, mentoring programmes, and richer analytics. In both cases, the strategic horizon is the same: close the distance between signal and support, iterate on what works, and protect the dignity and agency of learners. The result is not simply a more efficient school, but a more responsive one,capable of noticing when a student begins to drift and capable, just as importantly, of bringing that student back.

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