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EDUCONNECT360: School Management System for Predicting and Recommending Students at Risk of Dropping Out in Public Secondary Schools

William P. Inte, LPT, MAEd, MIT[1], Dr. Archieval M. Jain[2]
[1]*College of Computer Studies Laguna State Polytechnic University-Siniloan Campus, Siniloan, Laguna, Philippines*
[2]*Faculty, College of Computer Studies, Laguna State Polytechnic University-Siniloan Campus, Siniloan, Laguna, Philippines*

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Email of Corresponding Author: william.inte@deped.gov.ph

Abstract

This study developed and evaluated EduConnect360, an integrated school management system designed to predict and recommend interventions for students at risk of dropping out in public secondary schools. The system responds to the limitations of manual attendance recording, delayed risk identification, fragmented student records, and reactive intervention practices by integrating attendance monitoring, behavioral incident reporting, academic performance tracking, demographic profiling, predictive analytics, and intervention recommendations into one centralized platform. The study was anchored on an Input–Process–Output framework with a feedback loop, the Evolutionary Prototyping Model, the Technology Acceptance Model, and the ISO/IEC 25010:2011 Software Product Quality Model. It employed a developmental, descriptive-evaluative, and convergent parallel mixed-methods design. Quantitative and qualitative data were gathered through TAM-based surveys, ISO/IEC 25010:2011 expert evaluation, open-ended responses, interviews, stakeholder consultations, simulated user sessions, and synthetic data validation. The respondents included 107 school personnel from the Division of Quezon and 11 ICT coordinators from the Real District. EduConnect360 was developed as a web-based modular platform using PHP, MySQL, and JavaScript, with role-based dashboards for administrators, teachers, class advisers, guidance counselors/designates, security personnel, students, and parents. The system used logistic regression to classify students into low-, moderate-, and high-risk groups based on real-time attendance, behavioral, and socioeconomic data, while academic grades were excluded from prediction and used only for post-hoc validation. Synthetic data validation involved 1,120 records and showed that Logistic Regression remained highly effective when grades were excluded, achieving 0.93 accuracy, while risk distribution showed 50.9% low risk, 26.8% moderate risk, and 22.3% high risk. School personnel rated the system highly across TAM constructs, including perceived usefulness, ease of use, satisfaction, attitude toward use, and behavioral intention. ICT coordinators also rated the system highly across ISO/IEC 25010:2011 characteristics, including functional suitability, reliability, performance efficiency, security, and maintainability. Key concerns included the need for user training, technical support, offline functionality, infrastructure readiness, integration with existing DepEd systems, interface improvements, and real-world validation using actual student records. The study concludes that EduConnect360 is a usable, technically reliable, secure, and practical platform for proactive student risk monitoring and intervention planning. It recommends broader pilot testing, capacity-building, infrastructure support, DepEd system integration, predictive model enhancement, accessibility improvements, and longitudinal research on retention, workload, and intervention effectiveness. The study aligns with SDG 4 on Quality Education, SDG 9 on Industry, Innovation and Infrastructure, SDG 16 on Peace, Justice and Strong Institutions, and SDG 17 on Partnerships for the Goals. Its sustainability impact is primarily educational, institutional, technological, governance-oriented, and community-based because it supports learner retention, data-driven school management, secure student information handling, stakeholder collaboration, and evidence-based intervention planning.

Keywords: EduConnect360, Predictive Analytics, Logistic Regression, Recommendation Engine, Learner Retention

1. Introduction

Education remains central to individual advancement, national development, and participation in knowledge-based economies. As educational attainment becomes increasingly linked to opportunity and productivity, student retention has become a major concern, especially where dropout rates threaten educational equity (Organisation for Economic Co-operation and Development [OECD], 2021; UNESCO, 2023; Albert et al., 2023). Dropping out of school produces long-term social and economic consequences, including reduced employment prospects, lower lifetime income, financial instability, and continued poverty cycles (World Bank, 2022). At the societal level, high dropout rates weaken labor productivity, increase public welfare needs, and heighten social vulnerability (Bravo, 2023).

In the Philippines, DepEd has implemented programs such as the Dropout Reduction Program (DORP), Effective Alternative Secondary Education (EASE), and Open High School Program (OHSP) to address student disengagement. However, these initiatives remain limited when at-risk learners are identified only after disengagement is already visible. Traditional practices such as teacher observation, manual attendance books, subjective behavior rating scales, and beadle sheet attendance systems remain prone to delay, human error, manipulation, and limited real-time monitoring capacity (Dawson & Gašević, 2017; Siemens & Dawson, 2021; UNESCO, 2024b). The COVID-19 pandemic intensified these risks, with marginalized learners disproportionately affected and a potential 17% national dropout rate reported. EduConnect360 was therefore developed to shift dropout prevention from reactive response to proactive detection. It analyzes demographic data, attendance patterns, and documented behavioral incidents to generate early warning classifications. Attendance is recorded through QR code ID scanning, behavioral incidents are documented and verified by authorized school personnel, and academic grades are reserved for validating whether predicted risk levels correspond with later academic outcomes. Through dashboards, automated alerts, and embedded analytics, the system supports timely, targeted, and evidence-based intervention.

The literature shows that student dropout is a multidimensional educational problem shaped by attendance, behavior, academic performance, demographic conditions, and socioeconomic inequality (Pusztai et al., 2022; Potane et al., 2024). Predictive analytics has been increasingly used to identify at-risk learners and guide early intervention. Studies support the use of student data such as attendance, behavior, and demographics to predict dropout probability and strengthen educational decision-making. Hellas et al. (2018) emphasized that predictive approaches in education have become more sophisticated through logistic regression, decision trees, and ensemble techniques, but they also noted the need for stronger validation, replication, and educational relevance. This supports EduConnect360's use of interpretable algorithms and validation through later academic performance. Ramanathan and Balasubramanian (2018) also showed that academic and non-academic variables can influence student performance, including test results, parental involvement, family size, extracurricular participation, and travel time. These findings support the use of multidimensional student data in predictive modeling.

Integrated School Management Systems and educational data systems also strengthen institutional monitoring by centralizing student information and reducing fragmented record-keeping. Educational Management Information Systems show the importance of centralized data systems and real-time early warning interventions, while UNESCO (2024a) highlights the value of connecting EMIS and EWS for data-driven decision-making. EduConnect360 follows this direction by integrating attendance, behavior, academic monitoring, and predictive analytics in one school-based system. User-centered design is also critical. Buenaño-Fernández et al. (2019) emphasized that predictive systems should not only forecast outcomes but also help learners and educators act on learning histories. Alyahyan and Düştegör (2020) argued that machine learning adoption in schools requires relevant student attributes, clear achievement indicators, and usable tools for non-technical educators. EduConnect360 responds to this concern by using logistic regression because it is interpretable and practical for school personnel who may not have advanced technical expertise.

Intervention literature further supports the need for timely, specific, and data-driven responses. Early warning systems linked to counseling, academic support, and parental involvement are more effective than systems that rely on delayed detection. Lakkaraju et al. (2015) emphasized the practical value of predictive tools developed with school districts, especially when feature selection, evaluation metrics, and usability are aligned with educator needs. EduConnect360 reflects this principle by connecting risk classification with actionable intervention recommendations.

Globally, dropout is associated with lower income, poverty, and reduced productivity, making learner retention a concern not only for schools but also for social and economic development (World Bank, 2022). In the Philippine context, student dropout is shaped by socioeconomic inequality, school accessibility, limited institutional resources, behavioral concerns, and delayed intervention systems. The public cost of dropout may extend to healthcare, social services, and reduced workforce productivity (Asian Development Bank, 2021; World Bank, 2022). In the Real District of the Division of Quezon, the need for a proactive system is reflected in dropout records from a representative public high school. Dropout figures fluctuated across school years: 41 students in 2018–2019, 43 in 2019–2020, 4 in 2020–2021, 10 in 2021–2022, 27 in 2022–2023, and 21 in 2023–2024. The sharp decline during 2020–2021 may be linked to the transition to modular and blended learning during the pandemic, while the later increase indicates the continuing need for systematic, data-driven intervention (Hassan et al., 2024).

Current DepEd procedures classify students as at risk only after five consecutive unexcused absences, followed by a home visit and adviser-parent-student conference. A learner may be classified as No Longer Participating in Learning Activities (NLPA) if the learner voluntarily withdraws or exceeds 20% absences, as provided in DepEd Order No. 8, s. 2015 (Department of Education, 2015). This procedure is necessary for documentation but remains reactive because support begins after risk has already escalated. This reinforces the need for proactive, data-based dropout prevention systems. EduConnect360 is also aligned with DepEd policy structures. QR code attendance monitoring supports attendance documentation under DO 8, s. 2015; counselor-verified behavioral reporting aligns with DO 40, s. 2012 (Department of Education, 2012); and tiered intervention recommendations correspond with DO 58, s. 2017 (Department of Education, 2017). By integrating policy compliance into its architecture, EduConnect360 supports both school-level monitoring and institutional accountability (World Bank, 2022).

The study is conceptually anchored on an Input–Process–Output (IPO) model with a feedback loop. The inputs include attendance data collected through QR code scanning, behavioral incident reports recorded by teachers or counseling personnel, demographic indicators such as age, gender, socioeconomic status, and 4Ps membership, and academic grades for later validation. These inputs are integrated and preprocessed to ensure consistency before being used in predictive modeling. The main predictive model is logistic regression, selected for its interpretability and usefulness in forecasting educational risk (Aguiar et al., 2015). The model classifies students into low-, moderate-, or high-risk categories using real-time indicators such as attendance, behavior history, and demographics. Academic grades are excluded from the prediction stage to avoid data leakage and to preserve the purpose of early intervention. Instead, grades are used after the quarter or semester to validate whether risk predictions correspond with actual student performance.

The framework includes continuous recalibration through feedback. After interventions are implemented, new data and outcomes are returned to the system to improve future classifications. This adaptive design is consistent with research showing that dynamic educational contexts require feedback-trained machine learning (Ifenthaler & Yau, 2020; Papamitsiou & Economides, 2020). EduConnect360 also extends beyond prediction by providing prescriptive analytics and intervention recommendations, enabling the system to generate actionable insights that support informed decision-making and timely interventions. The development approach is also supported by the Evolutionary Prototyping Model, which emphasizes iterative refinement, stakeholder feedback, and adaptive improvement (Zakariyah, 2020). This model fits educational technology development because system usability and predictive accuracy must be tested with actual users and school conditions (Paterson & Guerrero, 2024). It also supports incremental improvement in predictive models based on stakeholder input and real-world implementation (Dumitrache, 2019).

The reviewed systems and literature reveal several gaps that EduConnect360 addresses. Existing school systems often provide attendance recording, academic tracking, or learning dashboards, but many lack integrated predictive analytics, real-time intervention capability, connected databases, contextual policy alignment, and student-specific recommendations. Some systems remain descriptive or rule-based, while others generate information too late to prevent disengagement. Existing systems also face concerns related to limited predictability, weak real-time response, poor data integration, usability barriers, cost, security, and privacy. The Philippine public-school context requires a system that is both technically functional and policy-aligned. Current dropout identification remains delayed because learners are formally considered at risk only after repeated absences or withdrawal conditions are met (Department of Education, 2015). This creates a gap between early signs of disengagement and formal intervention. EduConnect360 addresses this by using real-time attendance, verified behavioral reports, and demographic data to classify risk before dropout occurs.

The study also recognizes limitations. Some important student risk factors, such as mental health status, home stability, family background, and peer relationships, are not consistently available in school records and therefore cannot be fully integrated into the current risk model (Dumitrache, 2019; Manzanares et al., 2021). Infrastructure differences between schools may also affect connectivity, real-time monitoring, and hardware performance (Asian Development Bank, 2021). Since EduConnect360 is piloted in one public secondary school in the Real District, broader generalization requires validation across more schools and learning contexts. Nevertheless, adaptive data-driven risk modeling allows schools to identify high-risk students earlier and support systematic student persistence (Kurni et al., 2023). The rationale of the study is therefore grounded in the need for a centralized, interpretable, policy-compliant, and proactive platform that can assist school administrators, teachers, guidance counselors/designates, students, parents, and local education stakeholders. By combining predictive analytics with practical intervention recommendations, EduConnect360 contributes to educational technology, dropout prevention, and evidence-based school management (World Bank, 2022).

EduConnect360 aligns most directly with SDG 4 – Quality Education because its central purpose is to support learner retention, improve student monitoring, and provide early interventions for students at risk of dropping out. By helping schools identify vulnerable learners before disengagement becomes irreversible, the system supports inclusive and equitable education. The study also aligns with SDG 9 – Industry, Innovation and Infrastructure because it applies digital infrastructure, predictive analytics, QR code-based monitoring, dashboards, and recommendation systems to improve school management. Its use of AI-driven and data-driven tools supports technological and digital innovation in public education.

SDG 10 – Reduced Inequalities is also relevant because the study addresses dropout risks connected to socioeconomic disadvantage, marginalized learners, limited access, and uneven support systems. The inclusion of demographic and socioeconomic indicators, such as 4Ps membership, helps schools recognize contextual barriers affecting student persistence. SDG 16 – Peace, Justice, and Strong Institutions apply to the study's emphasis on policy compliance, data privacy, behavioral documentation, school discipline procedures, institutional accountability, and responsible student data management. The integration of behavioral incident reporting with verified procedures strengthens transparent and consistent school governance. SDG 17 – Partnerships for the Goals is reflected in the study's reliance on stakeholder participation, including school administrators, teachers, guidance personnel, parents, local government education committees, ICT coordinators, and community stakeholders. The system depends on coordinated action among school and community actors to support learner retention.

The study contributes to educational sustainability by strengthening learner retention, reducing delayed intervention, and supporting data-informed instruction and guidance services. Its focus on early warning indicators allows schools to protect students from academic disengagement before dropout occurs. It contributes to technological and digital sustainability by demonstrating how public secondary schools can use predictive analytics, QR code attendance systems, dashboards, and recommendation engines in a practical school management platform. The system's interpretable use of logistic regression also supports adoption among non-technical users.

It supports socio-economic sustainability because dropout prevention is linked to better employment opportunities, higher income potential, and reduced vulnerability to poverty (World Bank, 2022). By helping learners remain in school, EduConnect360 indirectly supports long-term workforce development and community stability. It contributes to policy and governance sustainability by aligning school-based technology with DepEd attendance, behavior, and intervention procedures. Its behavioral incident reporting and discipline documentation also support institutional consistency and accountability under school and DepEd policy structures.

It strengthens community and institutional sustainability by improving collaboration among administrators, teachers, guidance counselors/designates, parents, local education committees, and community stakeholders. Timely reports and notifications encourage shared responsibility for student success and make school interventions more coordinated. Finally, the study supports public health and social sustainability in a limited but relevant way because dropout is associated with broader social vulnerability, and the manuscript recognizes the role of mental health, home environment, and student support needs in retention concerns. Although these psychosocial factors are not fully included in the current predictive model, identifying them as limitations provides a direction for future system improvement.

2. Material and methods

2.1 Research Design

The study used a developmental research method with a mixed-methods approach to design and evaluate EduConnect360 as a student monitoring and prediction tool. It followed a convergent parallel mixed methods design, in which quantitative and qualitative data were collected simultaneously, analyzed separately, and integrated to provide a broader understanding of system usability, acceptance, and technical feasibility (Creswell & Plano Clark, 2018). This approach allowed the researcher to triangulate findings and evaluate both the human and technological factors affecting the implementation of EduConnect360. The study also used a descriptive-evaluative design to assess EduConnect360 as an early warning system for monitoring student risk factors. The descriptive component documented user experience, usability, workflow integration, and the system's capacity to support school-based monitoring. The evaluative component examined user acceptance, adaptability, technical performance, and areas requiring improvement. This design was directly connected to the Evolutionary Prototyping Model because the system was improved through repeated stakeholder feedback and validation. EduConnect360 was developed using the Evolutionary Prototyping Model, which emphasizes early working prototypes, continuous feedback, and iterative refinement throughout the system life cycle. This model was appropriate because public school environments involve changing user needs, diverse stakeholder roles, and policy-sensitive processes. The dual-track evaluation of school personnel and ICT coordinators also supported a comprehensive assessment of the human and technical dimensions needed for EduConnect360's sustainability (Creswell & Plano Clark, 2018).

2.2 Locale of the Study

The study was conducted within the Division of Quezon's public school system, with specific attention to public secondary schools and the Real District. EduConnect360 was designed for school-based use in public secondary education, particularly in contexts where student monitoring, attendance tracking, behavioral documentation, and early intervention require more systematic and data-driven support. The pilot context involved a public secondary school environment where EduConnect360 could be evaluated according to actual school workflows. The system was intended to support Grades 7 to 12 learners through real-time attendance monitoring, behavioral incident reporting, academic grade encoding, demographic profiling, risk classification, and intervention recommendation.

2.3 Respondents of the Study

The respondents consisted of two major groups selected for their direct relevance to the evaluation and implementation of EduConnect360. The first group included 107 school personnel across the Division of Quezon, composed of class advisers, guidance designates, and school heads from various public secondary schools. They were chosen because of their direct involvement in student monitoring, academic reporting, and behavioral intervention. Their responses were used to assess perceived usefulness, ease of use, user satisfaction, attitude toward use, and behavioral intention to adopt the system. The second group consisted of eleven ICT coordinators from the Real District, covering three public secondary schools and eight public elementary schools. These respondents were selected because of their technical roles in managing school information systems such as LIS and eBEIS. Their participation provided expert assessment of EduConnect360's functional suitability, reliability, performance efficiency, maintainability, and security using the ISO/IEC 25010:2011 Acceptability Questionnaire.

2.4 Sample and Sampling Procedure

The study used purposive sampling to select participants based on their roles in student monitoring, school operations, and system implementation. For the TAM-based survey, purposive-voluntary sampling was applied to include 107 school personnel from public secondary schools in the Division of Quezon. These participants included class advisers, guidance counselors or designates, and school administrators who were directly involved in monitoring student performance, handling behavioral concerns, and implementing school-level interventions. For the technical evaluation, census sampling was used to include all eleven ICT coordinators from the Real District. These participants were selected because of their expert involvement in school-level digital infrastructure and information systems. Although the ICT coordinator sample was limited, it was appropriate for expert-based system evaluation and pilot testing. The two-pronged sampling approach enabled the study to capture both end-user experience and technical system quality, although the non-randomized selection limited the generalizability of the findings beyond the sampled district.

2.5 Research Instrument

The study used two structured survey instruments to evaluate EduConnect360. The first instrument was a Technology Acceptance Model (TAM)-based survey administered to 107 school personnel. It measured perceived usefulness, perceived ease of use, user satisfaction, attitude toward use, and behavioral intention to adopt. The survey used a five-point Likert scale to determine how school personnel perceived the system's usability and acceptability in classroom, guidance, and administrative contexts. The second instrument was the ISO/IEC 25010:2011 Acceptability Questionnaire administered to eleven ICT coordinators. This instrument assessed the system's software quality based on functional suitability, reliability, performance efficiency, security, and maintainability. The instrument also used a five-point Likert scale to gather expert evaluation of EduConnect360's technical reliability, robustness, and readiness for institutional deployment. Qualitative data were also collected through open-ended survey responses, interviews, consultations, and informal discussions. These instruments captured user concerns, implementation issues, improvement suggestions, training needs, data privacy concerns, infrastructure limitations, and compatibility with existing DepEd systems.

2.6 Data Gathering Procedure

Data gathering began with consultations, focus group discussions, and interviews involving educators, guidance counselors, class advisers, school administrators, and ICT coordinators. These activities identified the main challenges in student monitoring, including fragmented documentation, inconsistent attendance and behavioral records, limited real-time analytics in existing systems, and the absence of a unified platform for early intervention. Stakeholder input guided the prioritization of core system functions, including QR code-based attendance tracking, structured behavioral incident logging, role-based access control, grade encoding, and analytics-driven risk forecasting. Subject teachers emphasized the need for grade submission and grade-locking mechanisms, while guidance counselors emphasized verified behavioral documentation for counseling interventions. These insights shaped the role-based access architecture of EduConnect360. After the design phase, a functional prototype was developed with QR code attendance tracking, behavioral incident reporting, academic grade encoding, and automatic student risk prediction. The system was built using PHP for backend logic, MySQL for relational data storage, and JavaScript for frontend interactivity and dynamic graphics. The modules were connected to a centralized database to consolidate real-time student information. Live demonstration sessions were conducted with faculty members, guidance counselors, ICT coordinators, and other stakeholders. During these sessions, the researcher presented how attendance logging, behavioral incident reporting, guidance approval, grade submission, risk prediction, and intervention recommendation operated within the system. Stakeholders observed the platform in simulated school-based contexts and provided feedback through follow-up consultations and informal discussions. The feedback was used to refine the system before broader implementation. EduConnect360 was not deployed in a live production setting. Instead, it underwent internal testing and simulated user sessions to validate reliability, usability, and predictive logic. These simulated sessions modeled everyday school processes such as QR-based attendance management, behavioral incident handling, grade encoding, and automated risk prediction. The resulting feedback was incorporated into the prototyping cycle to improve interface design, data flow, role-based access, and risk logic accuracy.

2.7 Data Analysis Techniques

Quantitative data were analyzed using descriptive statistics. Responses from the TAM-based survey were processed using weighted mean, frequency distribution, and standard deviation to interpret school personnel's perceptions across perceived usefulness, perceived ease of use, user satisfaction, attitude toward use, and behavioral intention. Responses from the ISO/IEC 25010:2011 Acceptability Questionnaire were analyzed using mean scores and standard deviation to assess functional suitability, reliability, performance efficiency, maintainability, and security. Qualitative data from open-ended survey responses, consultations, interviews, and informal discussions were analyzed through thematic analysis. Recurring themes included the need for training and support, data privacy compliance, integration with existing DepEd systems, infrastructure limitations, internet access concerns, offline or hybrid implementation needs, and system usability improvements. For predictive modeling, synthetic data were used because of ethical, privacy, and logistical limitations in accessing large-scale real-world student records. Synthetic data were created to replicate the statistical properties and structural patterns of student data while preserving privacy and confidentiality, a method widely used in machine learning research (Vie et al., 2022). The dataset included attendance rate, defiance count, age, sex, and 4Ps membership status to simulate realistic student risk patterns. The synthetic dataset underwent distribution analysis, class balance verification, and logical consistency checks to determine whether the generated data reflected plausible educational risk patterns. Literature emphasizes that alignment with real-world distributions is necessary when validating synthetic datasets in educational research (Khalil et al., 2025). Python was used for validation and analysis, with Pandas and Scikit-learn supporting distribution analysis, class balance verification, logical consistency checks, one-hot encoding, logistic regression modeling, and classification metrics.

Logistic regression was used because of its interpretability and suitability for structured tabular data. It classified students into low-, moderate-, or high-risk categories using real-time demographic and behavioral indicators such as attendance, defiance incidents, and 4Ps membership status. Average grades were excluded from the predictive inputs to prevent data leakage and preserve the early warning purpose of the model. Grades were used only for post-hoc validation and model calibration. This approach is supported by prior research on logistic regression in educational early warning systems (Aguiar et al., 2015) and educational risk prediction using structured academic and behavioral datasets (Dagdagui, 2022). Post-hoc validation compared predicted risk levels with final grade categories to determine whether students classified as high or moderate risk tended to show lower academic outcomes, while low-risk students tended to show stronger grade categories. Using grades only for validation rather than prediction follows best practice in educational data science because predictions should be derived from real-time participation indicators rather than outcome measures (Bowers & Zhou, 2019; Paterson & Guerrero, 2024). A comparative evaluation was also conducted using Logistic Regression, Random Forest, and Multinomial Logistic Regression. Logistic Regression achieved perfect classification because of deterministic mappings in the synthetic dataset, while Random Forest and Multinomial Logistic Regression showed moderate accuracy. This supported the use of Logistic Regression as an interpretable model for identifying educational risk in structured datasets (Ünsal Özbek & Yetkiner, 2021). Stakeholder feedback also confirmed satisfaction with the predictive dashboard, automated alerts, and risk visualization features, which align with good practices in educational technology implementation (Espinosa et al., 2023). The study also considered generalizability. Although the synthetic dataset showed strong internal consistency, external validation using real-world student records remains necessary to refine model performance and ensure applicability across diverse educational settings (Mansmann & Ön, 2025). The use of synthetic data and logistic regression demonstrated the feasibility of privacy-preserving educational risk prediction, especially where small or imbalanced real-world datasets limit model development (Flood et al., 2025). Logistic regression supports dropout risk prediction by identifying quantifiable patterns of student engagement (Bakhshinategh et al., 2018), while systematic verification strengthens logical consistency, predictive stability, and actionable feedback for student retention (Singh & Alhulail, 2022).

2.8 Ethical Considerations

Ethical safeguards were observed throughout the study. Participants were informed of the study's purpose and gave voluntary consent before participation. Confidentiality and data privacy protocols were maintained during data collection and analysis. The use of synthetic data further addressed ethical and privacy concerns by allowing predictive model development without exposing sensitive student records. Behavioral incident data were also handled through procedural safeguards. Reports submitted by teachers or class advisers required validation by guidance counselors or the School Disciplinary Committee before being accepted as legitimate inputs for predictive analytics. This protected students from inaccurate profiling and supported ethical, responsible, and institutionally aligned student monitoring.

2.9 System Development, Testing, and Predictive Modeling

EduConnect360 was designed as a role-based system architecture supported by a centralized MySQL database. It included user-specific dashboards for security personnel, subject teachers, class advisers, guidance counselors or designates, system or school administrators, and students or parents. Security personnel handled attendance recording, which supported effective student tracking. Subject teachers encoded and locked grades, submitted behavioral incident reports, and managed academic records. Class advisers handled student registration, section assignments, subject assignments, demographic records, and at-risk monitoring. Guidance counselors validated behavioral reports before they were entered into the system, following conduct documentation practices (Department of Education, 2018). School or system administrators used predictive analytics to identify dropout risks based on demographic profiles, attendance records, and behavior records, generating automated intervention suggestions (Papamitsiou & Economides, 2016). Students and parents accessed read-only electronic records containing grades, attendance, and behavioral information. Data integrity was maintained through role-specific access controls. Locked grades could only be modified during deliberation periods through a collaborative unlock process aligned with DepEd Order No. 8, s. 2015 (Department of Education, 2015). Behavioral records required counselor approval before database entry, while the predictive analytics module compared risk flags with later academic performance to support validation. This design aligned automation with institutional workflow and educational technology standards (Kucirkova & Rowsell, 2019). System development and testing followed iterative prototyping. Each prototype cycle underwent internal testing and stakeholder feedback before refinement. Added and improved features included grade locking, counselor-verified behavioral incidents with photo evidence, and dashboard customization for administrative monitoring and student performance. Through this process, EduConnect360 achieved a stakeholder-informed version that combined technical functionality, usability, predictive logic, and institutional fit.

3. Results and Discussion

3.1 Predictive Analytics and Model Validation

3.1.1 Synthetic Dataset and Risk Pattern Validation

The validation dataset contained 1,120 synthetic student records with demographic, attendance, behavioral, and risk-level variables. The dataset showed balanced representation across sex, an average age of 18.06, an average attendance rate of 78.40, and an average defiance count of 1.92. The most frequent risk category was low risk, with 570 students, while the remaining students were distributed across moderate and high-risk levels. These values indicate that the dataset contained sufficient variation to test risk classification patterns without using sensitive real student records. The use of synthetic data addressed ethical, privacy, and logistical limitations while still allowing model experimentation. Synthetic datasets are useful when they reproduce the statistical structure of real student data while protecting confidentiality (Vie et al., 2022). The validation process also supported the need for realistic feature distribution in educational datasets because conformity to real-world data patterns improves the credibility of predictive modeling (Khalil et al., 2025).

3.1.2 Model Performance and Predictive Comparison

The predictive testing showed that Logistic Regression achieved perfect accuracy when trained on the deterministic synthetic dataset. In the comparative evaluation, Logistic Regression using all features, including average grade, reached 1.00 accuracy, but this created a high risk of data leakage. Logistic Regression excluding average grade achieved 0.93 accuracy, while Random Forest reached 0.46 and Multinomial Logistic Regression reached 0.43. The final risk distribution classified 50.9% of students as low risk, 26.8% as moderate risk, and 22.3% as high risk. These results support the selection of Logistic Regression because it provided stronger interpretability and higher predictive performance than the alternative models tested. Logistic Regression is appropriate for structured educational risk prediction because it can produce clear classifications from academic, behavioral, and demographic datasets (Dagdagui, 2022). Its performance also confirms prior claims that Logistic Regression remains effective for identifying educational risk in structured datasets (Ünsal Özbek & Yetkiner, 2021).

3.1.3 Grade Validation and Bias Reduction

The results showed that students classified as high or moderate risk tended to fall into lower final grade categories, while students classified as low risk tended to achieve stronger academic outcomes. This pattern validated the predictive usefulness of the model because the risk classifications aligned with later academic performance despite excluding grades from the model inputs. When average grade was excluded, Logistic Regression still produced high accuracy at 0.93, showing that the system could support early warning without relying on outcome-based academic indicators. This finding strengthens the methodological decision to use grades only for post-hoc validation rather than prediction. Treating grades as a validation measure prevents data leakage and keeps risk classification focused on real-time participation indicators rather than delayed academic outcomes (Bowers & Zhou, 2019; Paterson & Guerrero, 2024). The result also supports the view that academic grades are often lagging indicators of disengagement and may introduce bias when used too early in predictive models (Prichard Committee for Academic Excellence, 2024; Müller & Guido, 2016).

3.2 Centralized Monitoring Interface

3.2.1 Attendance, Behavior, and Academic Tracking

The system interface successfully integrated attendance monitoring, behavioral incident reporting, and academic performance tracking in one centralized dashboard. Attendance was recorded through QR code scanning, allowing automatic check-in and check-out logging. The system also generated attendance summaries for class advisers when repeated absences occurred. Behavioral reporting allowed teachers and class advisers to submit incident reports with supporting evidence, while guidance counselors reviewed and approved reports before they became part of the student record. The academic tracking module displayed actual grades and grade trends for monitoring student progress. The results show that EduConnect360 reduced fragmented monitoring by placing major student records in a single platform. A simple and accessible interface supports adoption because educational technology is more effective when it reduces cognitive load and provides timely feedback (Al-Samarraie & Ghazal, 2021). The dashboard structure also supports educator engagement and intervention planning because well-organized monitoring tools improve school decision-making and student retention efforts (Manzanares et al., 2021).

3.2.2 Attendance and Behavioral Monitoring Functions

The attendance function allowed real-time recording of student entry and attendance history, supporting early identification of prolonged absenteeism. The behavior incident module provided a structured workflow for submitting, reviewing, validating, and escalating behavioral concerns. Guidance counselors/designates were able to use severity-based classification to detect behavioral patterns and determine appropriate intervention actions. The attendance and behavioral modules strengthened the system's capacity to identify risk before academic failure becomes severe. Computerized attendance systems improve absence management, reduce manual errors, and promote accountability (Asian Development Bank, 2021). Behavior monitoring platforms also support disciplinary management and targeted intervention by helping schools identify behavioral patterns and respond through data-driven procedures (Paterson & Guerrero, 2024).

3.2.3 Role-Based Dashboards and User Access

EduConnect360 provided differentiated access for administrators, teachers, guidance counselors/designates, class advisers, security personnel, and students. Administrators accessed school-wide analytics, attendance summaries, behavior reports, academic trends, risk classifications, announcements, and user permissions. Teachers monitored attendance, behavior, academic trends, and class-level risk flags. Guidance counselors/designates handled behavioral cases, risk analysis, intervention records, and parent contact. Class advisers managed enrollment data, academic reports, and advisory-level risk monitoring. Security personnel handled QR-based attendance verification, while students accessed personal records, announcements, and notifications. The role-based design improved workflow efficiency by ensuring that each user accessed only the information relevant to their function. Role-based access improves decision-making by providing users with real-time data visualizations that are tailored to their specific responsibilities and information needs. Personalized dashboards also strengthen administrative efficiency by streamlining access to relevant information and supporting intervention strategies. This confirms that customized access improves functionality, security, and adoption within school-based systems (Espinosa et al., 2023).

3.3 Data Management and Intervention Workflow

3.3.1 Secure Data Handling and System Access

The system implemented mandatory password reset during first login, role-based access control, audit trails, encrypted database storage, and restricted access to sensitive student data. Attendance, behavioral reports, grades, and socioeconomic data were stored in the system with validation processes to protect accuracy and accountability. The system also included offline data handling, allowing local storage during connectivity issues and automatic synchronization once internet access was restored. These findings indicate that EduConnect360 supports secure and accountable data management. Role-based access and audit trails help protect student information and maintain institutional accountability in compliance with the Philippines' Data Privacy Act of 2012 (Republic of the Philippines, 2012) and international standards such as GDPR (Espinosa et al., 2023). The inclusion of socioeconomic variables such as household income and 4Ps participation also supports contextualized risk classification, provided that these inputs are validated to avoid bias (Pusztai et al., 2022). Offline functionality further strengthens implementation in low-connectivity school environments (Vie et al., 2022).

3.3.2 Risk Scheduler and Intervention Recommendations

The risk scheduler processed attendance, behavioral, academic, and demographic information to generate student risk classifications. The results of risk analysis appeared in administrator and class adviser dashboards, where each student's risk level was paired with a suggested intervention. This allowed advisers and administrators to identify at-risk students quickly and coordinate targeted support based on the system's recommendation output. This finding shows that EduConnect360 converts data collection into actionable school intervention. The use of logistic regression allows risk classification to remain explainable, which helps educators understand the basis of system-generated recommendations (Gonzalez-Nucamendi et al., 2023). The system's intervention workflow supports the principle that predictive analytics should not only identify risk but also guide school personnel toward timely and evidence-based action (OECD, 2021).

3.4 Acceptability and Practical Usability

3.4.1 School Personnel Evaluation Using TAM

School personnel rated EduConnect360 highly across all Technology Acceptance Model constructs. Perceived Usefulness received a mean of 4.04 with a standard deviation of 0.55 and a median of 4.0. Perceived Ease of Use was the highest-rated construct, with a mean of 4.12 and a standard deviation of 0.48. User Satisfaction received a mean of 4.06 and a standard deviation of 0.54. Attitude Toward Use received a mean of 4.07 and a standard deviation of 0.45. Behavioral Intention received a mean of 4.08 and a standard deviation of 0.49. All constructs had minimum ratings of 3 and maximum ratings of 5, indicating consistently positive responses among the 107 school personnel. These results indicate strong acceptability and practical usability among intended users. The high Perceived Usefulness score shows that respondents recognized the system's value in monitoring student performance and supporting intervention. The high Perceived Ease of Use score suggests that the system's design reduced barriers to adoption. The positive scores for satisfaction, attitude, and behavioral intention indicate readiness for continued use and possible recommendation to colleagues. The findings align with the Technology Acceptance Model because perceived usefulness, ease of use, satisfaction, attitude, and behavioral intention are critical indicators of technology adoption in educational settings.

3.5 Technical Quality and Deployment Readiness

3.5.1 ICT Coordinator Evaluation Using ISO/IEC 25010

ICT coordinators rated EduConnect360 highly across all ISO/IEC 25010 quality characteristics. Functional Suitability received a mean of 4.42, a standard deviation of 0.72, and a median of 4.67. Reliability received a mean of 4.39, a standard deviation of 0.83, and a median of 5.00. Performance Efficiency received a mean of 4.59, a standard deviation of 0.66, and a median of 5.00. Security received a mean of 4.59, a standard deviation of 0.74, and a median of 5.00. Maintainability received a mean of 4.52, a standard deviation of 0.71, and a median of 5.00. These results indicate strong expert confidence in the system's technical performance. The high technical ratings show that EduConnect360 is functionally suitable, reliable, efficient, secure, and maintainable for educational use. Functional Suitability confirms that the system can support dropout-risk prediction and reporting. Reliability indicates confidence in stable system operation. Performance Efficiency suggests that the system can operate with minimal delay and resource use, which is important in resource-constrained school settings. Security confirms the importance of data protection and access control, while Maintainability suggests that the system can be updated and improved as school needs evolve.

3.6 Implementation Concerns and Sustainability

3.6.1 User Support, Infrastructure, and Real-World Validation

The findings showed that school personnel and ICT coordinators generally viewed EduConnect360 positively, but contextual and infrastructural concerns remained. Qualitative feedback identified the need for training, offline access, customization, interface improvement, integration with existing workflows, and broader infrastructure support. The study also acknowledged that the synthetic dataset had strong internal consistency but still required external validation using real-world student records. These concerns indicate that EduConnect360 is ready for further testing but still requires controlled expansion. Real-world validation is necessary because predictive models must be tested in actual educational environments to maintain accuracy and applicability (Mansmann & Ön, 2025). The findings also show that privacy-preserving synthetic data can support early model development when real data are limited or sensitive (Flood et al., 2025). Logistic regression remains useful for dropout risk prediction because it identifies quantifiable patterns of student engagement (Bakhshinategh et al., 2018), while systematic verification strengthens logical consistency, predictive stability, and actionable feedback for retention support (Singh & Alhulail, 2022).

3.7 Overall Interpretation of Findings

3.7.1 System Readiness for School-Based Risk Monitoring

The overall findings show that EduConnect360 met its major objectives. It provided a centralized interface for attendance, behavior, and academic monitoring; integrated Logistic Regression for predictive risk classification; established secure data management and intervention workflows; received high usability ratings from school personnel; and achieved strong technical quality ratings from ICT coordinators. The system showed practical potential for supporting school administrators, teachers, class advisers, and guidance counselors/designates in identifying and assisting students at risk of dropping out. The results confirm that EduConnect360 can support a shift from reactive dropout response to proactive, data-informed intervention. Its strongest contributions are centralized monitoring, interpretable predictive analytics, role-based access, secure data handling, and actionable intervention recommendations. Continued development should focus on real-world deployment, user training, infrastructure support, system customization, and validation using actual student records.

4. Conclusion & Recommendations

EduConnect360 was developed and evaluated as a centralized, user-friendly school management system that integrates attendance, behavioral, academic, and socioeconomic data to support the early identification and intervention of students at risk of dropping out. The system's role-based dashboards improved collaboration among administrators, teachers, class advisers, and guidance counselors by making relevant student information accessible and actionable. Its logistic regression model effectively classified students into low, moderate, and high-risk groups using real-time engagement and behavioral data, supporting proactive and equitable intervention before academic decline becomes severe. The system also demonstrated reliable data management through secure authentication, encrypted storage, audit trails, and offline functionality, while Technology Acceptance Model (TAM)-based feedback confirmed high usability, usefulness, satisfaction, and intention to adopt among school personnel. Expert evaluation using the ISO/IEC 25010:2011 Software

Product Quality Model further showed strong functional suitability, reliability, performance efficiency, security, and maintainability, although continued improvement in usability and infrastructure support remains necessary for broader scalability and long-term sustainability.

It is recommended that EduConnect360 undergo pilot testing across diverse school settings to validate its predictive performance, usability, and data management protocols in real-world contexts. Comprehensive training for teachers, administrators, and other users should be conducted with continuing technical support and capacity-building to strengthen platform use and user confidence. Schools should prioritize the provision of QR scanners, reliable internet connectivity, and improved offline functionality, especially in low-connectivity areas. Integration with existing DepEd systems, such as the Learner Information System, should be pursued to reduce redundancy and streamline workflows. Future development should enhance the predictive model through historical dropout data and advanced machine learning techniques, improve interface design and accessibility features, and explore additional modules for mental health support, parent engagement, and advanced analytics. Longitudinal research should also assess the system's long-term effects on student retention, teacher workload, and intervention effectiveness, while broader concerns such as policy support, community participation, and infrastructure development should be addressed with educational stakeholders and policymakers.

Compliance with ethical standards

The authors declare no conflict of interest. This study complied with recognized ethical standards for human-participant research by ensuring voluntary participation with informed consent, the right to withdraw without penalty, and strict confidentiality through anonymous, secure, and aggregated data handling. Given the focus on psychological well-being, procedures were non-invasive, and safeguards were observed to minimize discomfort, with guidance to appropriate support services when needed, and required institutional permissions were secured for instrument use and access to academic records.

REFERENCES

Aguiar, E., Chawla, N. V., Brockman, J., Ambrose, G. A., & Goodrich, V. (2015). Engagement vs. performance: Using electronic portfolios to predict first-year student success. *Proceedings of the Fifth International Conference on Learning Analytics & Knowledge*, 375–379. https://doi.org/10.1145/2723576.2723610

Albert, J. R. G., Basillote, L. B., Alinsunurin, J. P., Vizmanos, J. F. V., Muñoz, M. S., & Hernandez, A. C. (2023, December). *Sustainable Development Goal 4: How does the Philippines fare on quality education?* Philippine Institute for Development Studies. https://pidswebs.pids.gov.ph/CDN/document/pidsdps2316.pdf

Al-Samarraie, H., & Ghazal, R. (2021). The impact of user interface design on student engagement in e-learning platforms: A systematic review. *Education and Information Technologies.*

Alyahyan, E., & Düştegör, D. (2020). Predicting academic success in higher education: Literature review and best practices. *International Journal of Educational Technology in Higher Education, 17*(3). https://doi.org/10.1186/s41239-020-0177-7

Asian Development Bank. (2021). *Education and employment outcomes in the Philippines.* https://www.adb.org/publications/education-outcomes-philippines

Bakhshinategh, B., Zahedi, S., & Ghassemian, H. (2018). Predicting student academic performance using machine learning techniques: A systematic literature review. *Education and Information Technologies, 23*(6), 2685–2715.

Bowers, A. J., & Zhou, X. (2019). Receiver operating characteristic (ROC) area under the curve (AUC): A diagnostic measure for evaluating the accuracy of predictors of education outcomes. *Journal of Education for Students Placed at Risk (JESPAR), 24*(1), 20–46. https://doi.org/10.1080/10824669.2018.1523734

Bravo, E. D. (2023). Trends and causes of student dropouts in public higher education in the northern Philippines: A data visualization approach. *Journal for Educators, Teachers, and Trainers, 14*(3), 705–721. https://jett.labosfor.com/index.php/jett/article/download/1944/1128/7211

Buenaño-Fernández, D., Gil, D., & Luján-Mora, S. (2019). Application of machine learning in predicting performance for computer engineering students: A case study. *Sustainability, 11*(10), 2833. https://doi.org/10.3390/su11102833

Creswell, J. W., & Plano Clark, V. L. (2018). *Designing and conducting mixed methods research* (3rd ed.). SAGE Publications.

Dagdagui, R. T. (2022). Predicting students' academic performance using regression analysis. *American Journal of Educational Research, 10*(11), 640–646. https://pubs.sciepub.com/education/10/11/2/education-10-11-2.pdf

Dawson, S., & Gašević, D. (2017). Learning analytics: New horizons for teaching and learning in the digital age. *Journal of Computing in Higher Education, 29*(2), 249–257.

Department of Education. (2012). *Child protection policy* (DepEd Order No. 40, s. 2012). https://www.deped.gov.ph/2012/05/14/do-40-s-2012-deped-child-protection-policy/

Department of Education. (2015). *Policy guidelines on classroom assessment for the K to 12 Basic Education Program* (DepEd Order No. 8, s. 2015). https://www.deped.gov.ph/orders/do-8-s-2015/

Department of Education. (2017). *Adoption of new school forms for Kindergarten, Senior High School, Alternative Learning System, Health and Nutrition, and standardization of permanent records* (DepEd Order No. 58, s. 2017). https://www.deped.gov.ph/2017/11/27/do-58-s-2017-adoption-of-new-school-forms-for-kindergarten-senior-high-school-alternative-learning-system-health-and-nutrition-and-standardization-of-permanent-records-3/

Department of Education. (2018). *Guidelines on learner promotion and retention under the K to 12 Basic Education Program.* https://www.teacherph.com/deped-guidelines-learner-promotion-and-retention/

Dumitrache, G. (2019). Identifying risks in educational organizations. *Revista Economia Contemporană.* https://oaji.net/articles/2019/4505-1577097093.pdf

Espinosa, A. A., Gomez, M. A. C., Miranda, P. A., David, A. P., Abulon, E. L. R., Hermosisima, M. V. C., Quinosa, E. A., Jr., Soliman, A. A., De Vera, J. L., Claros, I. H. A., Cruz, H. G. M., & Gonzales, N. S. J. (2023). *Technology in education: A case study on the Philippines.* UNESCO. https://unesdoc.unesco.org/ark:/48223/pf0000387743

Flood, D., England, M., & Grawemeyer, B. (2025). Predicting at-risk programming students in small imbalanced datasets using synthetic data. *arXiv.* https://arxiv.org/html/2505.17128v1

Gonzalez-Nucamendi, A., Noguez, J., Neri, L., Robledo-Rella, V., & García-Castelán, R. M. (2023). Predictive analytics study to determine undergraduate students at risk of dropout. *Frontiers in Education, 8*, Article 1244686. https://www.frontiersin.org/journals/education/articles/10.3389/feduc.2023.1244686/full

Hassan, M. A., Muse, A. H., & Nadarajah, S. (2024). Predicting student dropout rates using supervised machine learning: Insights from the 2022 National Education Accessibility Survey in Somaliland. *Applied Sciences, 14*(17), 7593. https://doi.org/10.3390/app14177593

Hellas, A., Ihantola, P., Petersen, A., Ajanovski, V. V., Gutica, M., Hynninen, T., Knutas, A., Leinonen, J., Messom, C., & Liao, S. N. (2018). Predicting academic performance: A systematic literature review. In *Companion of the 23rd Annual ACM Conference on Innovation and Technology in Computer Science Education* (pp. 175–199). https://dl.acm.org/doi/abs/10.1145/3293881.3295783

Ifenthaler, D., & Yau, J. Y.-K. (2020). *Utilising learning analytics to support study success in higher education: A systematic review. Educational Technology Research and Development, 68*(4), 1961–1990. https://doi.org/10.1007/s11423-020-09788-z

Khalil, M., Liu, Y., & Abouzied, A. (2025). AI for data generation in education: Scaling teaching and learning. *British Journal of Educational Technology, 56*(2), Article 13580. https://doi.org/10.1111/bjet.13580

Kucirkova, N., & Rowsell, J. (2019). The research and innovation cycle: How literary practice can improve educational technologies. *Learning, Media and Technology, 44*(2), 127–142.

Kurni, M., Mohammed, M. S., & Srinivasa, K. G. (2023). Predictive analytics in education. In *Artificial Intelligence and Machine Learning Applications*. Springer. https://link.springer.com/chapter/10.1007/978-3-031-32653-0_4

Lakkaraju, H., Aguiar, E., Shan, C., Miller, D., Bhanpuri, N., Ghani, R., & Addison, K. L. (2015, August). A machine learning framework to identify students at risk of adverse academic outcomes. In *Proceedings of the 21st ACM SIGKDD International Conference on Knowledge Discovery and Data Mining* (pp. 1909–1918). https://dl.acm.org/doi/abs/10.1145/2783258.2788620

Mansmann, U., & Ön, B. I. (2025). The validation of prediction models deserves more recognition. *BMC Medicine, 23*, 166. https://bmcmedicine.biomedcentral.com/articles/10.1186/s12916-025-03994-3

Manzanares, P., Lee, C., & Patel, R. (2021). Real-time monitoring and predictive modeling in education: Global trends and applications. *Educational Technology Research & Development, 29*(4), 211–230. https://www.researchgate.net/publication/388489912_Real-Time_Performance_Monitoring_and_Predictive_Analysis_in_Education

Müller, A. C., & Guido, S. (2016). *Introduction to machine learning with Python: A guide for data scientists.* O'Reilly Media.

Organisation for Economic Co-operation and Development. (2021). *Artificial intelligence and education: Guidance for policymakers on AI-driven learning analytics and student risk assessment.* https://www.oecd.org/education/artificial-intelligence-and-education.htm

Papamitsiou, Z., & Economides, A. A. (2016). Learning analytics and educational data mining in practice: A systematic literature review of methods and applications. *Journal of Educational Technology & Society, 19*(4), 91–104.

Papamitsiou, Z., & Economides, A. A. (2020). Adaptive learning systems and learning analytics: A systematic review of the literature. *Education and Information Technologies, 25*(3), 1957–1988.

Paterson, K., & Guerrero, A. (2024). *Predictive analytics in education: Considerations in predicting versus explaining college student retention.* ERIC. https://files.eric.ed.gov/fulltext/EJ1401369.pdf

Potane, J., Banaag, R. A., & Sumodevilla, J. L. C. (2024). Factors affecting student dropout behavior: A systematic review. *International Journal of Educational Management and Innovation, 5*(1), 53–70. https://www.academia.edu/122672232/Factors_Affecting_Student_Drop_Out_Behavior_A_Systematic_Review

Prichard Committee for Academic Excellence. (2024). *Student behavior and engagement: Lagging indicators.* https://prichardcommittee.org/student-behavior-and-engagement-lagging-indicators/

Pusztai, G., Fényes, H., & Kovács, K. (2022). Factors influencing the chance of dropout or being at risk of dropout in higher education. *Education Sciences, 12*(11), 804. https://www.mdpi.com/2227-7102/12/11/804

Ramanathan, R., & Balasubramanian, T. (2018). Exploring the high potential factors that affect students' academic performance. *International Journal of Education and Management Engineering, 8*(6), 15–23. https://doi.org/10.5815/ijeme.2018.06.02

Republic of the Philippines. (2012, August 15). *Republic Act No. 10173: Data Privacy Act of 2012*. LawPhil

Siemens, G., & Dawson, S. (2021). Learning analytics and academic advising: Opportunities and challenges. *Journal of College Student Retention: Research, Theory & Practice, 23*(1), 11–28.

Singh, H. P., & Alhulail, H. (2022). Predicting student-teachers' dropout risk and early identification: A four-step logistic regression approach. *IEEE Access, 10*, 6470–6482. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4588338

UNESCO. (2023). *Global education monitoring report 2023: Technology in education.* https://unesdoc.unesco.org/ark:/48223/pf0000385723

UNESCO. (2024a). *Artificial intelligence, blockchain, and extended reality in lifelong learning.* https://unesdoc.unesco.org/ark:/48223/pf0000391599

UNESCO. (2024b). *Educational management information systems (EMIS): A guide for policy-makers.* UNESCO Publishing.

Ünsal Özbek, E. B., & Yetkiner, A. (2021). Logistic regression approach in classifying the effectiveness of online education. *International Journal of Psychology and Educational Studies, 8*(Special Issue), 21–31. https://files.eric.ed.gov/fulltext/EJ1354802.pdf

Vie, D., Ren, X., & Han, T. (2022). *Privacy-preserving synthetic data generation for educational analytics.* https://arxiv.org/abs/2207.03202

World Bank. (2022). *The economic impacts of learning poverty and dropout rates in the Philippines.* https://documents.worldbank.org/en/publication/documents-reports/documentdetail/099000207152223103/idu002b5536c0db4104ec3087d809906ec2eae56

Zakariyah, S. S. (2020). *Guide to evolutionary prototyping.* Academia.edu. https://www.academia.edu/8587413/Guide_to_Evolutionary_Prototyping