

A Proposed Information System Model for Decision Support in Early Identification and Intervention of Technical Student Dropout Risk

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Abstract—Student dropout remains a significant challenge in engineering and technical higher education, where technical students are expected to meet demanding academic, practical, technological, and professional learning requirements. This study proposes an educational information system model for the early identification of technical students at risk of dropout and for supporting timely academic intervention. The study combines a Systematic Literature Review (SLR) guided by PRISMA with Design Science Research Methodology (DSRM) to develop the proposed model as a research artifact. The literature synthesis shows that existing dropout models remain limited in integrating academic and non-academic data, developing interpretable multidimensional risk profiles, and translating predictive outputs into actionable intervention recommendations. The proposed model integrates academic records, Learning Management System activity, socioeconomic conditions, psychological indicators, social support, and institutional information with risk profiling, hybrid machine learning, Explainable Artificial Intelligence, prescriptive analytics, and human-in-the-loop validation. Rather than treating dropout prediction as a purely computational task, the model positions educational data and artificial intelligence as decision-support tools for identifying risk factors, informing academic interventions, and maintaining human oversight in final decisions. The study contributes a human-centred decision-support framework for proactive academic advising and student progression in engineering and technical education.

Keywords—early warning system, human-in-the-loop, information system, student dropout.

I. INTRODUCTION

Student dropout remains a significant challenge in higher education, including engineering and technical education, because it affects student progression, academic achievement, the efficiency of academic services, and institutional quality (Vaarma & Li, 2024). Dropout among technical students cannot be understood solely as a consequence of academic performance because it may result from interactions among academic, administrative, socioeconomic, psychological, and learning-environment factors (Oqaidi et al., 2022). These multidimensional conditions require systematic identification and timely intervention. From the perspective of educational

information systems, integration of data and decision-support features may allow institutions to detect new risks, comprehend the underlying causes of these risks, and implement the required academic interventions (Carballo-Mendivil et al., 2025).

In Indonesia, dropout among students also represents a significant issue in terms of higher education. Statistics on higher education for the year 2025 have shown that there were 289,670 students who dropped out of their studies, which was an increase of 2.62% compared to the previous year. In West Java, private higher education institutions represented 86.67% of dropouts based on types of institutions, which amounted to 44,512 students who dropped out of studies, equaling 6.63% of the total number of students enrolled in private higher education institutions in West Java. Statistics from 2021-2025 show that the dropout rate of private higher education institutions in West Java was reduced from 7.33% in 2021 to 4.27% in 2022 before rising to 6.63% in 2025.

Digital transformation has expanded the volume and variety of educational data available to higher education institutions, particularly in technical and vocational settings where digital and technological competencies are increasingly important (Shahroni et al., 2022; Anwar & Minghat, 2024). Academic records, administrative information, Learning Management System (LMS) activity, attendance records, learning outcomes, and student-support information can potentially be used to identify students experiencing academic difficulties. Such data can support learning analytics, early warning systems, and evidence-based academic decision-making, while also supporting institutional adaptation to technology-rich technical education environments (Hashim et al., 2024). However, their practical use frequently remains centred on administrative storage rather than integrated analytical processes capable of identifying, interpreting, and managing student dropout risk (Oqaidi et al., 2022). For engineering and technical education, the effective use of these data is particularly relevant to supporting technical students' continued participation and progression in academically and professionally demanding programmes.

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Previous studies have demonstrated the potential of machine learning and learning analytics for identifying students at risk of dropout. Existing models have incorporated academic, administrative, demographic, socioeconomic, attendance, study-history, and LMS-related variables to improve early risk identification (Vaarma & Li, 2024; Oqaidi et al., 2022; Hoca & Dimililer, 2025). These studies demonstrate that multi-source educational data can provide useful evidence for identifying students who may require academic attention. Other research has also shown that dropout risk can involve combinations of academic and non-academic factors rather than a single predictor (Realinho et al., 2022).

Despite these developments, most existing approaches remain focused primarily on risk classification or prediction. Limited attention has been given to integrating academic and non-academic information into interpretable multidimensional student risk profiles, explaining the factors underlying individual risk conditions, and translating predictive outputs into actionable intervention recommendations that can be reviewed by academic stakeholders. Existing models may identify which students are at risk but provide less support for determining why the risk has emerged and what academic response may be appropriate (Hoca & Dimililer, 2025; Realinho et al., 2022). This restriction is critical within technical education because the problem of dropping out should be aimed not only at retaining students but also at keeping them engaged with technical knowledge and professional training, which are essential to the preparedness of students for their future (Khakimova, 2025).

Three research gaps are emphasised in this study: limited integration of academic and non-academic student data, insufficient development of interpretable multidimensional risk profiles, and limited translation of analytical outputs into actionable academic interventions. Addressing these gaps requires an educational decision-support model that connects risk identification with risk interpretation and human-validated intervention. Hybrid machine-learning approaches offer a potential analytical basis because student profiling and risk estimation can be combined to generate more informative risk information than risk classification alone. When complemented by Explainable Artificial Intelligence (XAI), prescriptive analytics, and human oversight, these analytical outputs can provide academic stakeholders with information for understanding student conditions and selecting appropriate interventions.

Therefore, this study proposes an educational information system model for the early identification and intervention of technical student dropout risk. The model integrates multi-source educational data, student risk profiling, risk-level estimation, risk-factor interpretation, prescriptive intervention recommendations, and human-in-the-loop validation to support proactive and evidence-based academic decision-making. Rather than treating dropout prediction as a purely computational task, the proposed model positions educational data and artificial intelligence as decision-support tools that assist academic advisors,

programme administrators, counselors, and other stakeholders while retaining human judgment in final decisions. The contribution of this study to engineering and technical education lies in extending learning analytics from predictive identification toward human-centred academic decision support for technical student progression and timely educational intervention.

II. METHOD

This study is conducted in two main phases: a Systematic Literature Review (SLR) and the Design Science Research Methodology (DSRM). The first phase seeks to discover and synthesize research advancements in connection with student dropout predictions, early warnings, learning analytics, machine learning, Explainable AI, and academic interventions. The results of the systematic literature review will form the basis of theory and empirics for discovering research gaps and requirements of the proposed model. The second phase uses DSRM to construct an Information System model for detecting student dropout risks as the research artifact. By the end of this phase, the results of the literature review are transformed into an integrated model for supporting risk identification, student profiling, risk factors analysis, and academic intervention.

A. Systematic Literature Review (SLR)

This stage of the study involves conducting a Systematic Literature Review (SLR), which is based on the PRISMA protocol to provide a transparent and systematic approach to identifying and selecting relevant literature. For the purposes of the study, the Scopus bibliographic database has been used to conduct the literature search among the journal articles and conference proceedings published from 2021 to 2026. Three different search strategies have been developed using Boolean operators for the identification of literature on the following themes: student attrition risk, combination of academic and non-academic factors, and use of hybrid machine learning techniques combined with Explainable AI. As part of the literature selection, the following steps have been conducted: duplicate exclusion, metadata screening, screening of titles and abstracts, and finally full-text review according to the predefined eligibility criteria. After that, 67 papers have been selected for literature synthesis, gap analysis, and model development.

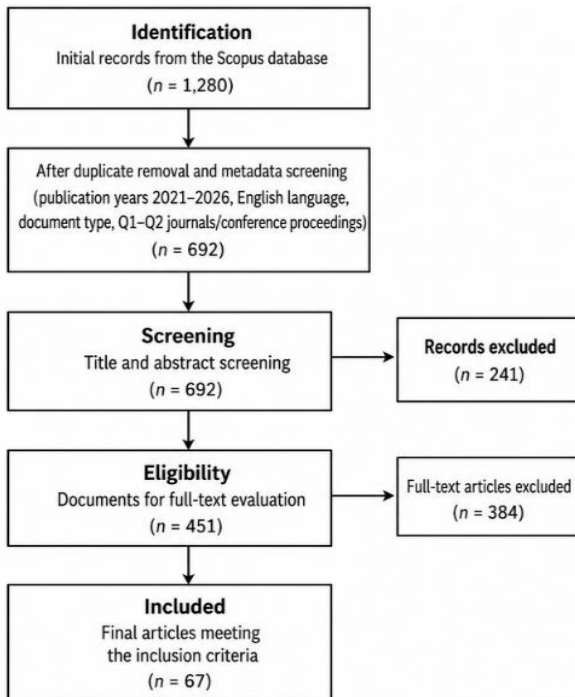


Fig. 1. PRISMA Diagram.

B. Design Science Research Methodology (DSRM)

The second phase of this study applies the Design Science Research Methodology (DSRM) to develop an early detection model as the research artifact (Adam et al., 2021). The process begins with the identification of the research problem based on the findings and research gaps identified in the first phase. The objective of this phase is to develop a decision-support Information System model capable of generating student risk profiles and providing intervention

recommendations based on integrated data. The artifact is developed through the integration of multi-source data, risk profiling and prediction, Explainable Artificial Intelligence, prescriptive analytics, and human-in-the-loop validation.

The proposed model is subsequently demonstrated through application scenarios involving academic advisors, study program administrators, counselors, and educational administrators. Its performance is evaluated based on the clarity of the risk information generated, the usefulness and relevance of the intervention recommendations, alignment with academic and organizational processes, readiness for multi-source data integration, and the usability of the human-in-the-loop mechanism. Finally, the communication stage is conducted through academic publication presenting the design of the proposed model, its theoretical contributions, and its potential policy and practical implications. The overall DSRM process is presented in Figure 2.

III. RESULTS AND DISCUSSION

The systematic literature review (SLR) of 67 selected studies published between 2021 and 2026 indicates that research on the early detection of student dropout has predominantly employed machine learning and learning analytics techniques to process and analyze educational data. Nonetheless, current studies have been mainly concerned with discovering at-risk students rather than providing any predictive ability to help with proactive decision-making concerning academics. Using academic and non-academic information, profiling risks, causal reasoning, and making early intervention suggestions still represent the main difficulties that arise when trying to create an effective early warning system based on data.

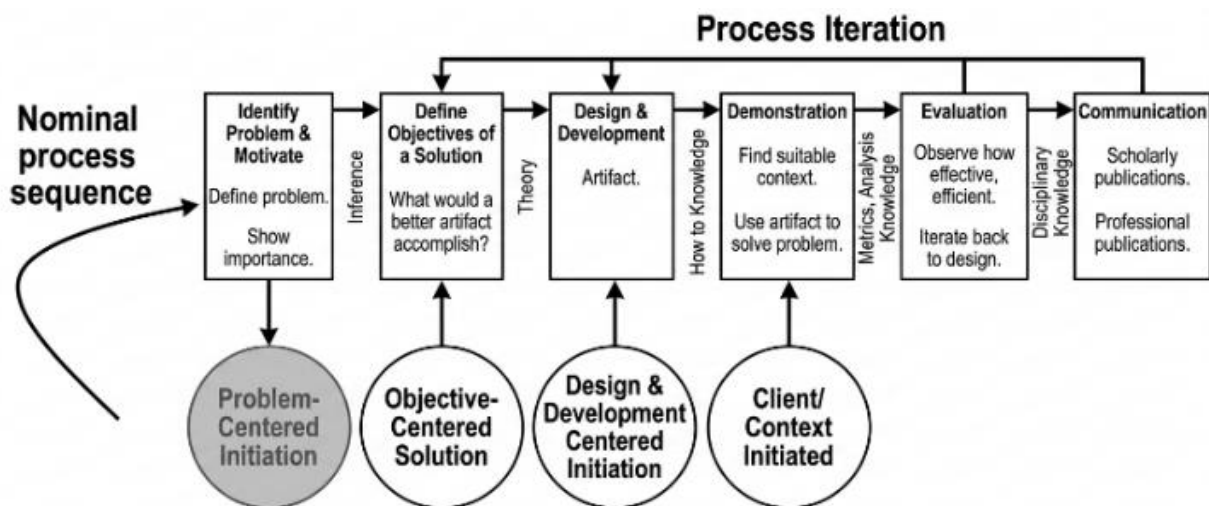


Fig. 2. Design Science Research Methodology (DSRM).

This paper conducts a state-of-the-art (SOTA) review of the available literature by building connections between different works depending on the used model, the type of data, and the objective of analysis. The studies considered were finally grouped into five broad groups as follows: (1) predictive models based on supervised machine learning

algorithms; (2) learning analytics models based on data extracted from learning management systems (LMSs); (3) early warning models built based on the first features of the students; (4) multidimensional models involving both academic and non-academic dimensions; and (5) explainable and interpretable models aimed at improving the

interpretability of predictions. These groups and their synthesis are shown in Table I below.

Different approaches have been developed for the detection of early signs of risk of dropout of students in the earlier literature. For instance, different models have been designed based on different kinds of data that are related to both educational and administrative activities. In addition, learning analytics have been implemented using LMS data. Some early warning systems have considered initial characteristics of students, while other approaches have implemented models that combine academic and non-academic factors. Additionally, some Explainable Artificial Intelligence (XAI) approaches have been proposed for the early detection of dropouts. Despite all developments that have been made in this area, many of the studies have been devoted to solving different problems separately, such as risk identification, making predictions, or interpreting the results. Specifically, data integration from multiple sources, student risk profiles, explanation of factors that affect risk, and recommendations for interventions have not been well investigated yet.

As a result of the literature review, three main research gaps were revealed, related to the implementation of predictive analytics, risk profiling, and decision-making in order to prevent student dropout. This will form the foundation for the research direction and the model being proposed in this study. These gaps are summarized in Table II.

With regard to the revealed gaps, this study presents the information system model for the early identification of the risk of students' dropout with special focus on academic decision support. In particular, this model involves the use of academic, LMS activity, socio-economic, and psychological data in order to create a holistic view of the students' risk profiles. The analytical part of the model, which consists of hybrid machine learning, Explainable Artificial Intelligence (XAI), and prescriptive analytics, is aimed at predicting the risk of dropout, determining and interpreting the risk factors, and generating intervention recommendations. The above recommendations are further validated using a human-in-the-loop method to enable inclusion of expert judgement in the decision-making process. As such, the model under development is more than just the ability to identify students at risk; rather, it provides insights that will help the academic institution's management in choosing the right intervention approach. The overall structure of the model proposed can be seen in Figure 3 below. The model under consideration is viewed as the

abstract design of the information system architecture that helps to detect and make decisions about potential cases of student dropout. The components of the model are organized to demonstrate logical connections between different blocks of concepts, rather than a sequence of actions.

This model involves a number of data sources such as academic data and non-academic data. In regard to academic data, it is important to note that the indicators of the academic performance and progress of students are considered. Non-academic data, on the other hand, involves LMS activities, socio-economic status, psychology, social support, learning environment, and institutional engagement of the students. All the above data sources collectively form the basis upon which the analytical components produce the risk intelligence needed for academic decision-making.

The analytical components of the proposed model involve risk profiling, estimation of risk levels, integration of analytical results, interpretation of risk factors through explainable artificial intelligence, and generation of early intervention recommendations. In the current case, risk profiles and intervention recommendations constitute conceptual components of the proposed model since they have not been developed through the use of empirical data. Risk profiles in this case are the risk categories to be determined by the model after its implementation. Intervention recommendations, on the other hand, depict how the prescriptive analytics part can help the academics to choose intervention methods.

The generated recommendations are not intended to serve as automated decisions but rather as decision-support outputs that require validation through a human-in-the-loop mechanism. Academic advisors, study program administrators, counselors, or student affairs officers are expected to review and validate these recommendations before any formal academic decision is made.

To maintain a balance between academic and non-academic factors, the model incorporates several feature domains derived from the Academic Information System, Learning Management System (LMS), administrative and student affairs data, as well as student questionnaires, as presented in Table III. Psychological variables in this study are used as self-reported non-academic indicators to support the early detection of student dropout risk rather than for psychological diagnosis or clinical assessment. The validation of psychological information and subsequent intervention decisions are conducted by academic stakeholders or counselors in accordance with the human-in-the-loop mechanism.

TABLE I
STATE OF THE ART.

Model Category	Related Articles	Data/Features Utilized	Approach	Limitations
Supervised ML-based student risk and dropout prediction	Azizah et al. (2024); Cho et al. (2023); Kim et al. (2023); Oqaidi et al. (2022); Sathe and Adamuthe (2021)	Academic performance (GPA and completed credits), demographic characteristics, socio-economic information, and administrative records	RF, DT, SVM, LR, NB, KNN, and LightGBM	Primarily emphasizes predictive performance, while providing limited explanation of the factors contributing to individual student risk.
LMS and learning analytics-based prediction	Azizah et al. (2024); Liu et al. (2024); Park et al. (2025); Sartana et al. (2025); Vaarma and Li (2024)	LMS logs, Moodle activity, weekly clickstream data, digital learning behavior, assessment trends, engagement, and attendance	Learning analytics, CatBoost, LSTM-DNN, deep learning, and other predictive models	Relies strongly on academic and digital behavioral data, with limited integration of broader non-academic factors required for comprehensive intervention.
Pre-enrollment and early warning prediction	Carballo-Mendivil et al. (2025); Realinho et al. (2022)	Pre-enrollment information, demographic profiles, previous academic records, and early academic indicators	XGBoost, decision tree, and early risk classification	Early identification is possible, but predictions are largely based on static or early-stage information and provide limited support for adaptive interventions as student conditions change.
Multi-factor academic and non-academic prediction	Jaiswal et al. (2024); Zhang et al. (2026)	Academic performance, psychological conditions, stress, sense of belonging, family factors, social support, and related non-academic characteristics	Deep learning and statistical/multivariate analysis	Academic and non-academic factors are considered, but their integration into a unified and interpretable decision-support framework remains limited.
Explainable and interpretable student risk prediction	Arslan et al. (2026); Bettahi et al. (2025a); Čotić Poturić et al. (2025); Nagy and Molontay (2024); Shaikhanova et al. (2025)	Academic, cognitive, non-cognitive, demographic, workload, and individual student characteristics	XAI, SHAP, feature importance, scoring algorithms, and interpretable predictive models	Improves interpretation of risk factors, but the explanations are not consistently translated into specific and actionable intervention recommendations for educators.
Learning analytics and student-facing decision support	Fernandez-Nieto et al. (2021); Susnjak et al. (2022)	Multimodal learner data, learning activities, engagement indicators, and learner analytics	Learning analytics dashboards, multimodal analytics, visualization, and reflective feedback	Provides interpretable information and feedback to learners, but is not primarily designed as an integrated early-risk prediction and intervention system.
Mental-health-related explainable prediction	Pillai et al. (2024); She et al. (2022)	Psychological, behavioral, speech, and mental-health-related information	Explainable AI, multimodal prediction, and AI-based screening	Demonstrates the potential of explainable prediction for sensitive behavioral and psychological outcomes, but is not specifically designed for academic-risk prediction or technical student intervention.

TABLE II
MAIN RESEARCH GAPS BASED ON THE SLR RESULTS.

No	Research Gap	Literature Findings	Implications for Research	Related Articles
1	Limitations in data sources	Existing student risk and dropout models remain predominantly dependent on academic, administrative, and LMS-based data, while psychological, socio-economic, and broader non-academic factors have not been consistently integrated.	Develop a multi-source data framework integrating academic performance, LMS activity, socio-economic characteristics, psychological conditions, and other relevant non-academic variables.	Bettahi et al. (2025a); Jaiswal et al. (2024); Vaarma and Li (2024); Zhang et al. (2026)
2	Limitations in modeling approaches	Supervised learning is widely used for student risk classification, but most models focus on assigning students to predefined risk classes and provide limited representation of heterogeneous or multidimensional student risk profiles.	Develop a hybrid ML approach combining clustering for student risk profiling with supervised classification for risk prediction.	González-Pérez et al. (2025); Hoca and Dimililer (2025); Kim et al. (2023); Shaikhanova et al. (2025)
3	Limitations in decision-support capabilities	Existing models commonly stop at risk identification or prediction, while explanations of underlying risk factors and actionable intervention recommendations remain limited.	Integrate XAI-based interpretable modeling with prescriptive analytics to generate targeted and actionable intervention recommendations.	Arslan et al. (2026); Nagy and Molontay (2024); Shaikhanova et al. (2025); Susnjak et al. (2022)
4	Limited integration of explainability and intervention	Explainable models can identify influential variables and individual risk factors, but these explanations are rarely translated into intervention strategies that can be directly implemented by educators.	Establish a mechanism linking explainable risk factors with specific intervention actions, priorities, and follow-up strategies.	Arslan et al. (2026); Bettahi et al. (2025b); Nagy and Molontay (2024); Čotić Poturić et al. (2025)
5	Limited adaptive and longitudinal risk assessment	Many early-warning models rely on static or early-stage data and do not continuously update student risk profiles as academic performance, engagement, and personal conditions change.	Develop an adaptive longitudinal prediction framework capable of updating student risk profiles and intervention priorities using continuously accumulated data.	Azizah et al. (2024); Carballo-Mendivil et al. (2025); Sartana et al. (2025); Vaarma and Li (2024)

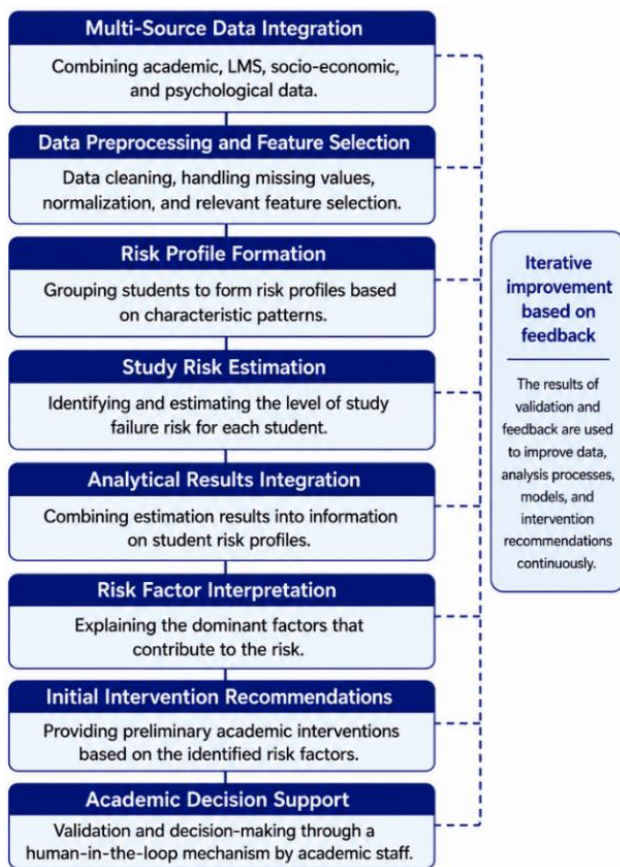


Fig. 3. Proposed Framework for Early Detection of Student Dropout Risk and Academic Decision Support.

Table III demonstrates that the proposed model does not rely solely on academic indicators but also incorporates digital learning behavior, socioeconomic status, psychological factors, social support, and the institutional environment as inputs for generating risk intelligence and early intervention recommendations. Based on the proposed conceptual risk profiles, the model provides alternative early intervention recommendations as part of its prescriptive analytics component. However, because this study is currently at the model design stage, these recommendations have not yet been generated through an implemented clustering process or validated using empirical data. Instead, they serve as conceptual illustrations of how the proposed system can translate student risk-profile information into actionable alternatives to support academic decision-making. All recommendations remain subject to review and validation through the human-in-the-loop mechanism before being applied to individual students, as presented in Table IV.

Table IV illustrates how the prescriptive recommendation component of the proposed model maps each risk profile to relevant early intervention alternatives. This mapping remains conceptual and is intended to illustrate the implementation of the recommendation

component within a decision-support system rather than represent the output of an implemented clustering process or empirical validation. Consequently, the recommendations are not automatically generated; instead, they are intended to serve as decision-support inputs that require further validation by academic stakeholders through a human-in-the-loop mechanism. This approach ensures that final decisions continue to consider the academic context, individual student circumstances, ethical considerations, and institutional policies.

The above-mentioned proposed model is likely to enhance the role of AIS in terms of not only administering data but also providing decision support on an academic level. By means of integrating academic data with other types of information, risk profiling, risk factor interpretation, and alternative courses of action in case of need for early intervention, the proposed model is likely to provide greater academic risk intelligence to the academic advisors and study programs. This ability would enable the early detection of those students who could be in danger of being excluded from the university and the appropriate preventive action to be taken in advance.

This suggested model is based on the findings of existing studies about the early prediction of dropouts (Carballo-Mendivil et al., 2025; Oqaidi et al., 2022; Vaarma & Li, 2024). Previous literature has established that it is possible to detect at-risk students using academic, demographic, socioeconomic, LMS, and psychological variables (Hoca & Dimililer, 2025; Oqaidi et al., 2022; Realinho et al., 2022; Vaarma & Li, 2024). Despite that, currently available tools do not place enough emphasis on decision-making rather than the predictive capacity itself (Hoca & Dimililer, 2025; Park et al., 2025; Sartana et al., 2025).

As compared to conventional approaches in machine learning, the suggested model uses academic and non-academic data within one Information System framework (Bettahi et al., 2025b; Jaiswal et al., 2024; Zhang et al., 2026). Such integration allows for the creation of a multidimensional risk profile that gives an understanding of students' vulnerability beyond GPA requirements (Čotić Poturić et al., 2025).

Moreover, the inclusion of techniques such as SHAP and LIME for Explainable AI (XAI) mitigates the interpretability issue of the black box models by highlighting the main factors that influence the probability of student dropout (Arslan et al., 2026; Bettahi et al., 2025a; Nagy & Molontay, 2024). The suggested model links the interpretable risk factors to specific measures through the implementation of early intervention actions (Shaikhanova et al., 2025; Susnjak et al., 2022). In order to ensure that decisions are made ethically and not overly dependent on algorithmic outcomes, the human-in-the-loop component of the model ensures that the final decisions remain with academic advisors, study programs, and counselors (Adam et al., 2021; Shaikhanova et al., 2025).

TABLE III
CANDIDATE FEATURES AND DATA SOURCES FOR THE PROPOSED MODEL.

Feature Domain	Example Indicators	Data Sources
Academic	GPA/Semester GPA, completed credits, failed courses, attendance, academic status	Academic Information System, course registration cards (KRS)/academic transcripts (KHS), official transcripts, attendance records
LMS / Digital Learning Behavior	LMS logins, access duration, late assignments, quiz/forum participation, course material access	LMS logs, assignment data, quizzes, forums, digital activity recaps
Socio-Economic	Study financing, scholarships, payment delays, device/internet access	Financial records, scholarship data, student affairs database, questionnaires
Psychological	Academic stress, motivation, self-regulation, self-efficacy, resilience, burnout	Self-report questionnaires using relevant psychological instruments
Social Support	Family/peer support, communication with academic advisors, mentoring	Questionnaires, advising logs, student affairs/counseling service data
Environmental and Institutional	Residential status, learning conditions, campus activities, academic/counseling services	Questionnaires, student affairs database, activity logs, academic service records

TABLE IV
CANDIDATE FEATURES AND DATA SOURCES FOR THE PROPOSED MODEL.

Risk Profile	Dominant Factors	Early Recommendations from the Model	Human-in-the-Loop Validation & Decision-Making Actors
Low Risk	Stable academic progress, active LMS engagement, low stress levels	Periodic monitoring and motivation reinforcement	Academic advisor / Study program
Academic Risk	Low GPA/Semester GPA, credit deficiency, failed courses	Academic advising, tutoring, study plan evaluation	Academic advisor / Study program
Digital Learning Engagement Risk	Low LMS logins, late assignments, low digital participation	LMS monitoring, assignment reminders, learning assistance	Course instructor / Academic advisor
Socio-Economic Risk	Financial constraints, employment/working, limited device/internet access	Scholarship information, administrative support, academic flexibility	Study program / Student affairs / Finance department
Psychological Risk	High stress levels, low motivation, burnout, weak self-regulation	Counseling, mentoring, psychological support	Counselor / Academic advisor
Social Support Risk	Low family/peer support, minimal communication with academic advisor	Peer support, mentoring, academic communication enhancement	Academic advisor / Counselor / Student affairs

With the help of the above process, the model will be able to increase the capacity of the Academic Information System (AIS) to make the AIS go beyond its conventional role as an administrative system for storing data to become a more proactive decision-making system that relies on risk intelligence (González-Pérez et al., 2025; Shaikhanova et al., 2025). The new system does not only rely on storing the student's data but instead aims at changing the multi-sourced data into useful risk information and possible interventions.

The implications of this study include the following:

- (i) Advancing the literature on learning analytics by demonstrating the importance of integrating academic, digital learning behavior (LMS), socioeconomic, and psychological data to develop a more comprehensive understanding of student dropout risk through multi-source intelligence (Jaiswal et al., 2024; Vaarma & Li, 2024; Zhang et al., 2026).
- (ii) Connecting XAI outputs with prescriptive intervention strategies by extending the application of educational AI beyond model interpretability toward the formulation of actionable intervention alternatives (Arslan et al., 2026; Bettahi et al., 2025a; Nagy & Molontay, 2024; Shaikhanova et al., 2025).
- (iii) Contributing to the Design Science Research literature on the ethical application of AI by emphasizing a human-centered approach in which AI augments rather than replaces human pedagogical judgment and decision-making (Adam et al., 2021; Shaikhanova et al., 2025).
- (iv) Extending the function of traditional student information systems (SIKAD) from primarily static data management toward proactive decision support

based on integrated student risk intelligence (González-Pérez et al., 2025; Susnjak et al., 2022).

- (v) Supporting a shift from one-size-fits-all policies toward risk-profile-specific interventions, such as financial assistance or LMS-based academic coaching, thereby enabling more targeted allocation of institutional resources (Hoca & Dimililer, 2025; Shaikhanova et al., 2025).

CONCLUSION

This study aimed to develop an Information System model for the early detection of student dropout risk to support timely and informed academic decision-making. The model was developed using a Systematic Literature Review (SLR) and the Design Science Research Methodology (DSRM) to address limitations identified in previous studies, particularly their predominant focus on risk identification, limited integration of academic and non-academic factors, and insufficient support for risk interpretation and intervention recommendations. The proposed model integrates academic data, Learning Management System (LMS) activity, socioeconomic status, psychological indicators, social support, and the institutional environment to generate comprehensive student risk intelligence. Its analytical components combine hybrid machine learning, Explainable AI (XAI), and prescriptive analytics to develop student risk profiles, identify factors contributing to dropout risk, and formulate early intervention alternatives. Accordingly, the proposed Academic Information System (AIS) extends beyond its conventional role in data management by providing decision support based on interpretable risk intelligence and intervention

recommendations, which remain subject to review and validation by academic stakeholders through a human-in-the-loop mechanism. The proposed model represents a conceptual research artifact derived from the SLR findings and DSRM process; therefore, its empirical implementation, performance evaluation, and validation using real-world student data have not yet been conducted and constitute important directions for future research.

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