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Toward AI-Assisted Early Academic Risk Detection in Introductory Physics Courses: Interpretable Profiling among First-Year Engineering Students

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ABSTRACT

Early academic risk detection in first-year engineering education requires approaches that are not only predictive, but also interpretable and actionable for instructors, tutors, and student-support teams. This study examines how multidimensional student data can be used to generate interpretable academic-risk profiles among first-year engineering students enrolled in introductory physics courses. Data were collected from 691 students at a private multi-campus university in Mexico across three academic cohorts. A baseline questionnaire covering academic preparation, perceived previous knowledge, study habits, well-being, academic status, contextual indicators, and subject relevance was linked to first-month course grades using course-based codes and de-identified before analysis. The analysis combined exploratory explanatory modeling and Chi-square Automatic Interaction Detection to identify variables and profile patterns associated with early academic performance and first-month academic risk. The results showed that early performance was associated with prior high-school average, perceived sufficiency of previous knowledge, academic status, homework completion, sleeping hours, time management, scholarship context, cohort-related variation, and perceived subject relevance. The study synthesized four interpretable academic-risk profiles: preparation gap, self-regulation difficulty, contextual compound risk, and motivation-relevance risk. The study also proposes a conceptual AI-assisted early-support framework connecting student indicators, interpretable profiles, traffic-light decision support, AI-assisted tutoring mechanisms, human-in-the-loop governance, and follow-up recalibration. The findings provide an empirical basis for future AI-assisted early-alert strategies, while emphasizing that the proposed framework is conceptual and requires validation with recent cohorts before operational implementation.

KEYWORDS Academic risk detection; first-year engineering; interpretable machine learning; learning analytics; CHAID; structural equation modeling; AI-assisted support.

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Introduction

First-year engineering education represents a critical transition period in which students must adapt to new academic expectations, increased workload, independent study routines, and demanding foundational courses. Introductory physics courses are particularly important in this context because they provide conceptual and analytical foundations for later engineering subjects. However, early underperformance in these courses may signal difficulties related not only to academic preparation, but also to study habits, self-regulation, well-being, motivation, and institutional context.

Universities increasingly use learning analytics and artificial intelligence to identify students who may be academically at risk. These approaches can support early-warning systems, academic advising, tutoring, and student-support interventions. Nevertheless, many predictive models focus mainly on classification accuracy and provide limited explanation of why a student or group has been identified as at risk. In educational contexts, this lack of interpretability is problematic because risk labels may influence academic decisions, support allocation, and student perceptions. Therefore, early academic-risk detection should not only predict low performance, but also generate transparent and actionable information for instructors, tutors, and support teams.

This issue is especially relevant in foundational physics courses for first-year engineering students. Low early grades may result from different combinations of factors. For example, one student may struggle because of insufficient prior academic preparation, while another may struggle with time management, sleep, motivation, or academic status. Treating all students with low performance as a single homogeneous group may lead to generic interventions that do not respond to their specific needs. Interpretable profiling can help address this limitation by identifying different patterns of academic vulnerability and linking them to differentiated forms of support.

Building on this need, the present study examines how multidimensional student data can be used to generate interpretable academic-risk profiles among first-year engineering students enrolled in introductory physics courses. The study uses data from 691 students at a private multi-campus university in Mexico, collected across three academic cohorts. The study linked baseline questionnaire data from Physics I and Introduction to Physics to first-month course grades using course-based codes, and the dataset was de-identified before analysis in *Physics I* and *Introduction to Physics*. The analysis combines exploratory explanatory modeling and Chi-square Automatic Interaction Detection to identify variables and profiles associated with early course performance and first-month academic risk.

The study is guided by two research questions:

RQ1: Which academic, behavioral, contextual, motivational, and well-being-related variables are associated with early academic performance in introductory physics courses among first-year engineering students?

RQ2: How can interpretable profiling identify combinations of student characteristics associated with first-month pass/fail classification in introductory physics courses?

The contribution of this paper is threefold. First, it identifies multidimensional variables associated with early academic performance in introductory physics courses. Second, it synthesizes these variables into interpretable academic-risk profiles: preparation gap, self-regulation difficulty, contextual compound risk, and motivation-relevance risk. Third, it proposes a conceptual AI-assisted early-support framework in which interpretable profiles can inform traffic-light alerts, tutoring recommendations, and human-in-the-loop academic support. The study does not claim to deploy or validate an operational AI system; rather, it provides an empirical and interpretable basis for future AI-assisted early-alert strategies in first-year engineering education.

The remainder of this paper is organized as follows. Section II presents the theoretical background, focusing on early academic risk in first-year engineering education, AI-enabled learning analytics and early alert systems, and the role of interpretable risk profiling for actionable support. Section III describes the methodology, including the study context, instrument, variables, data preparation, and analytical strategy. Section IV reports the results and synthesizes the CHAID-based interpretable academic-risk profiles. Section V discusses the implications of the findings and introduces the conceptual AI-assisted early-support framework. Finally, Section VI presents the conclusions, methodological considerations, and future research directions.

Theoretical background

Early Academic Risk in First-Year Engineering Education

First-year engineering education is a critical transition period in which students must adapt to new academic expectations, higher workload, independent study routines, and foundational disciplinary requirements. Courses such as mathematics and physics often play a central role in this transition because they provide the conceptual and analytical basis for later engineering subjects. Previous studies have shown that early achievement, prior academic preparation, institutional conditions, and students' capacity to adapt to university life influence persistence and success in engineering programs [1]. In this context, academic risk should not be understood only as an individual deficit, but as the result of interactions among preparation, study behavior, well-being, motivation, and institutional support.

Recent research also highlights the importance of looking beyond grades alone. Engineering students may experience workload pressure, academic stress, and well-being challenges that affect their learning experience and performance [2]. At the same time, students who experience early academic failure may still persist when adequate support structures are available, suggesting that early risk detection should be connected to timely and differentiated support rather than used only for classification [3]. This is especially relevant in first-year physics and mathematics courses, where early underperformance can provide an important signal for academic support and progression monitoring. Studies focused on engineering courses have therefore argued for risk-based approaches that identify students who may require support before academic difficulties become harder to reverse [4], [5].

AI-Enabled Learning Analytics and Early-Alert Systems

Learning analytics and artificial intelligence have increasingly been used to identify students exposed to academic risk and to support early decision-making in higher education. Early-warning systems can help institutions detect students who may be struggling during the first weeks of study and provide evidence for academic advising, tutoring, or other forms of support when combined with appropriate institutional processes. Recent work on first-year academic performance prediction shows the potential of early-warning models to support institutional monitoring and timely action [6]. Similarly, studies on course-level prediction indicate that academic performance can be modeled using student data to identify risk patterns in specific learning contexts [5].

However, the educational value of AI-enabled learning analytics depends on more than model accuracy. Recent reviews show that many AI-based educational tools and dashboards still face limitations related to real-world implementation, evaluation quality, privacy, bias, transparency, and weak integration between prediction and intervention [7]–[9]. In practice, a system that only assigns a risk score may be insufficient for instructors, tutors, or student-support teams, because they need to understand the nature of the risk and select an appropriate response. Therefore, early alert systems require approaches that translate student data into meaningful and actionable information.

Interpretable Risk Profiling for Actionable Support

The need for explainable and interpretable approaches has become increasingly important in educational data mining and learning analytics. Predictive models may classify students as at risk, but complex models do not always show why a particular student or group has been flagged. This is problematic in education, where risk labels can influence support decisions and where transparency is important for trust, fairness, and responsible use. Recent studies on explainable learning analytics, course-success prediction, AI-based learning tools, and AI-supported academic support suggest that educational AI should combine prediction, interpretability, feedback, and pedagogical action rather than rely solely on model accuracy [8], [10]– [12].

Explainable artificial intelligence has been used to improve the interpretation of academic performance models by identifying the factors that contribute to success or failure. Ujkani et al. [12], for instance, used machine learning and deep learning techniques to predict course completion and identify at-risk students, applying SHAP to explain the factors behind model outputs. Their results showed that student engagement and registration timing were important factors for performance, illustrating how XAI can support more targeted educational interventions. Nevertheless, for many educational settings, highly complex explanations may still be difficult to translate into practice. Interpretable models, such as decision trees, remain useful because they can generate transparent rules and profiles that are easier for tutors and support teams to understand.

Building on this literature, the present study focuses on interpretable academic-risk profiling rather than opaque prediction. It combines exploratory explanatory modeling with CHAID-based decision-tree profiling to identify combinations of academic, behavioral, contextual, motivational, and well-being-related variables associated with early performance in introductory physics courses. This approach responds to the need for learning analytics that are not only data-driven, but also transparent and actionable for tutors and student-support teams. The study therefore provides an empirical basis for future AI-assisted early-support strategies, while avoiding claims of fully validated prediction or automated intervention.

Methodology

The study is positioned as an empirical learning analytics contribution. It combines explanatory modeling and interpretable CHAID-based profiling to identify academic, behavioral, contextual, motivational, and well-being-related indicators associated with early course performance. The resulting profiles are intended to inform future AI-assisted early-alert and support strategies, but this study did not implement or evaluate an operational AI system.

Instrument Development and Study Context

The research instrument was developed through an exploratory phase conducted during the August–December 2016 and January–May 2017 academic periods with 100 undergraduate engineering students. This phase was used for item generation, refinement, and identification of possible factors associated with failure in first-year physics courses. It did not involve an experimental intervention or manipulation.

The main field study was conducted at a private multi-campus university in Mexico. The sample included 691 first-year engineering students enrolled in common

introductory physics courses: *Physics I* and *Introduction to Physics*. Data were collected across three academic cohorts: August–December 2017, January–May 2018, and August–December 2018. The two courses were analyzed together because they represent foundational physics experiences in the first-year engineering curriculum and because the original analysis found insufficient evidence to treat their score distributions as substantially different.

Although the dataset corresponds to pre-pandemic cohorts, the aim of this conference paper is not to claim direct operational deployment in current AI systems. Instead, the study uses an existing multidimensional dataset to examine how interpretable academic-risk profiling can provide an empirical basis for future AI-assisted early-alert models. Such models should be re-estimated and validated with more recent cohorts before institutional implementation.

Instrument, Variables and Outcome

Data were collected using a baseline questionnaire administered at the beginning of the course, before the first academic evaluation. The instrument comprised 39 questions and 49 coded items covering academic preparation, perceived prior knowledge, physical well-being, family and social context, academic development, previous educational experience, social development, organization and study habits, and perceived relevance of physics to the engineering career.

Questionnaire responses were linked to first-month course grades using course-based codes, and the dataset was de-identified before analysis. The first-month grade was used as the early academic performance outcome. For the profiling analysis, early academic risk was operationalized through low early performance and first-month pass/fail classification based on predefined grade thresholds, rather than institutional dropout. For the profiling analysis, early academic risk was operationalized through low early performance and first-month pass/fail classification based on predefined grade thresholds, rather than institutional dropout.

The main variables later retained in the explanatory and profiling stages included semester, scholarship type, academic status, prior high-school grade average, perceived sufficiency of previous knowledge, homework completion during the senior year of high school, sleeping hours, self-evaluation of time management, and perceived importance of the subject for the student's career.

Data Preparation and Analytical Strategy

Data preparation included scale verification, consistency checks, missing-data screening, category harmonization, and recoding of categorical variables when required for statistical analysis. The final analytical sample included 334 students from *Introduction to Physics* and 357 students from *Physics I*, resulting in a combined sample of 691 students.

Given the heterogeneous nature of the questionnaire data, association measures were selected according to the measurement level of each variable. Spearman's rho was applied to ordinal or non-normally distributed variables; polychoric and tetrachoric coefficients were used for ordinal–ordinal and binary–binary associations, respectively; biserial or point-biserial coefficients were considered for relationships involving a continuous outcome and a dichotomous variable; and Cramér's V was used for nominal categorical associations. This strategy preserved the structure of the original variables rather than forcing all questionnaire items into a single statistical format.

The analytical strategy followed four stages. First, descriptive statistics and association analyses were used to examine relationships between student characteristics and early course grades. Second, exploratory path analysis /SEM-based explanatory modelling was applied as a procedure to identify variables associated with early academic performance [13]. Third, significant and theoretically meaningful variables were analyzed using Chi-square Automatic Interaction Detection to generate course non-passing risk [14]. Fourth, Shapiro–Wilk, Mann–Whitney U, and Kruskal–Wallis tests were used to examine normality and grade differences across relevant groups.

The SEM and CHAID results were interpreted as exploratory and explanatory evidence. No claim is made that the resulting tree constitutes an externally validated predictive model.

Figure 1 summarizes the analytical workflow used in the study. The process begins with the baseline questionnaire and continues through data cleaning, association analysis, exploratory SEM, CHAID-based profiling, non-parametric group comparisons, and the synthesis of interpretable academic-risk profiles.

Students received an explanation of the purpose of the study and provided informed consent. Participation was voluntary and did not affect course evaluation. The questionnaire did not request directly identifying information such as student name, student ID, or email address. The original project was reviewed by the Institutional Research and Ethics Review Committee of Tecnológico de Monterrey. Course-based codes were used to link questionnaire responses with first-month grades, and the dataset was de-identified before analysis.

Results and Interpretable Risk Profiles

Overview of Early Academic Performance

The first stage of the analysis examined the distribution of first-month grades in *Physics I* and *Introduction to Physics*. The overall mean grade was 72.92, with a standard deviation of 17.86 and a coefficient of variation of 24.49%. The Shapiro–Wilk test indicated that grades were not normally distributed ($W = 0.95221$, $p \leq 0.05$), supporting the use of non-parametric tests for group comparisons.

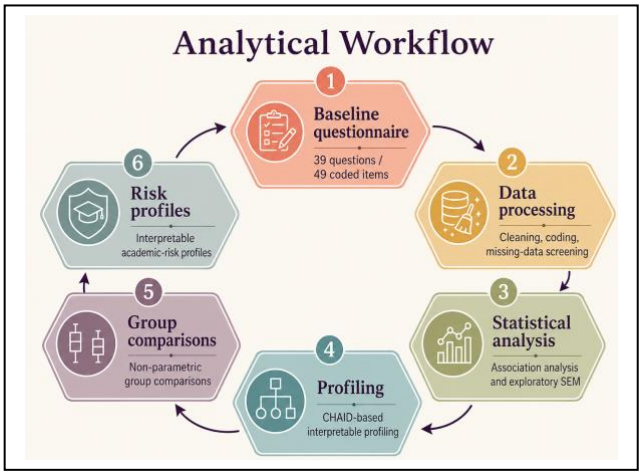


Fig. 1. Methodology for the interpretable academic-risk profiling.

These results show that early course performance varied substantially across the sample. Since the first-month grade was used as the outcome variable, the analysis focused on early academic performance, low early performance, and first-month academic risk, rather than institutional dropout. This distinction is important because the objective of the study was to generate interpretable risk profiles that could inform early academic support in foundational physics courses.

Variables Retained for Risk Profiling

The exploratory modeling process retained nine variables associated with early academic performance: semester, scholarship type, academic status, prior high-school grade average, perceived sufficiency of previous knowledge, homework completion during the senior year of high school, sleeping hours, self-evaluation of time management, and perceived importance of the subject for the student's career. These variables were retained in the final explanatory model and later used to support the interpretation of CHAID-based risk profiles. The model was re-evaluated from eleven initially significant variables to nine final explanatory variables.

Together, Table I and the group comparisons address RQ1 by identifying the variables associated with early academic performance. Students in the August–December 2017 cohort obtained the lowest mean grade (69.80), while students in January–May 2018 and August–December 2018 obtained mean grades of 73.96 and 75.63, respectively. Academic status also differentiated early performance, with conditional-status students obtaining a lower mean grade (63.28) than academic-support students (71.29) and regular students (74.07).

Preparation-related differences were also observed: students with a prior high-school average of 80 or below obtained a mean grade of 60.64, compared with 73.98 for those above 80, and students reporting insufficient previous knowledge obtained a lower mean grade (68.32) than those reporting sufficient knowledge (76.83).

Table 1. Main variables retained for interpretable academic-risk profiling

Variable	Evidence	Risk-profiling interpretation
Semester (V1)	Kruskal-Wallis = 12.444, p = 0.0019; SEM p = 0.003	Cohort-related variation
Scholarship type (V13)	SEM p = 0.011	Contextual compound risk
Academic status (V14)	Kruskal-Wallis = 15.339, p = 0.0004; SEM p = 0.010	Prior academic vulnerability
Prior high-school average (V19)	Mann-Whitney U = 10302, p < 0.05; SEM p < 0.001	Preparation gap
Perceived previous knowledge (V20)	Mann-Whitney U = 42739, p <= 0.05; SEM p < 0.001	Perceived preparation gap
Homework completion (V23)	Kruskal-Wallis = 31.579, p <= 0.05; SEM p = 0.022	Prior study-habit risk
Sleeping hours (V30)	Kruskal-Wallis = 19.087, p = 0.0007; SEM p = 0.020	Well-being-related risk
Time management (V47)	Kruskal-Wallis = 49.413, p <= 0.05; SEM p < 0.001	Self-regulation risk
Subject relevance (V49)	Kruskal-Wallis = 19.876, p <= 0.05; SEM p = 0.004	Motivation-relevance risk

Note. SEM = Structural Equation Modeling. The Results section discusses detailed group patterns

Behavioral and well-being-related indicators also showed relevant differences. Students reporting 61–80% homework completion in senior high school obtained a lower mean grade (63.86) than those reporting 81–100% completion (74.84). Students sleeping fewer than three hours had a low mean grade (51.38), while those sleeping between eight and ten hours had the highest mean grade (77.16). Although the group reporting more than ten hours of sleep had an even lower mean grade, this subgroup was very small and should not be overinterpreted. Time management followed a similar pattern, with students reporting bad organization obtaining lower mean grades (62.00) than those reporting excellent organization (81.77). Finally, perceived subject relevance was also associated with early performance: students who strongly disagreed that the subject was important obtained a mean grade of 64.10, compared with 75.11 among those who strongly agreed.

Scholarship type showed differentiated descriptive patterns and was retained in the SEM model. Students with sports scholarships, SEDENA scholarships, and no scholarship showed lower mean grades than several other scholarship groups; however, these subgroup patterns should be interpreted cautiously because they are context-specific and may reflect institutional conditions, selection effects, or additional unmeasured factors.

CHAID-Based Interpretable Risk Profiles

The CHAID analysis identified how selected explanatory variables combined in relation to pass/fail course outcomes. In the original analysis, the response variable was the student grade, which was dichotomized into passed and failed categories using two alternative thresholds. Under Criterion 1, students with a grade of 75 or above were classified as passing, while those below 75 were classified as failing. Under Criterion 2, students with a grade of 70 or above were classified as passing, while those below 70 were classified as failing. In both criteria, the CHAID results showed that non-passing profiles were not explained by a single variable, but by combinations of contextual, preparation-related, behavioral, and cohort-related indicators.

Under Criterion 1, the analysis identified failure-associated profiles involving students with SEDENA or sports scholarships, students without scholarships, and students reporting insufficient prior preparation, in combination with injury status and cohort period. Additional failure-associated profiles involved students with other scholarship types who had failed subjects in high school, or students without previous failed subjects but with a high-school average of 80 or below. Under Criterion 2, similar patterns were observed, again combining scholarship type and insufficient preparation, but also including low frequency of nutritious meals before the first daily activity, previous failed subjects, cohort period, and prior high-school average.

The two thresholds were used as sensitivity criteria to examine whether the identified risk patterns remained consistent under alternative definitions of early non-passing status. The 70-point threshold reflects a more permissive early-performance criterion, whereas the 75-point threshold represents a stricter criterion for identifying students requiring early academic support.

These findings address RQ2 by showing how interpretable machine-learning profiling can identify combinations of student characteristics associated with pass/fail course outcomes.

For this research paper, the CHAID outputs were synthesized into four interpretable academic-risk profiles. These profiles should be interpreted as evidence-informed analytical labels rather than mutually exclusive operational categories. They synthesize evidence from the explanatory model, group comparisons, and CHAID terminal patterns. Therefore, a student could show indicators associated with more than one profile, and the profiles should not be used as automatic assignment rules without further validation. Instead, they provide a transparent way to summarize different combinations of risk indicators that may require different types of support:

- Preparation gap: students whose risk is mainly associated with lower prior achievement, insufficient perceived previous knowledge, or previous failed subjects identified in the CHAID profiles.
- Self-regulation difficulty: students whose risk is linked to weaker study habits, lower homework completion, or weaker time-management self-evaluation.
- Contextual compound risk: students whose risk appears through combinations of academic status, scholarship context, cohort-related variation, or other institutional/contextual indicators.
- Motivation-relevance risk: students whose lower performance is associated with weaker perceived relevance of physics to their engineering career.

Figure 2 summarizes these four interpretable academic-risk profiles and the main indicator types associated with each. Rather than reproducing the full CHAID trees, the figure provides a more accessible representation of the patterns identified in the exploratory profiling stage.

This synthesis preserves the empirical basis of the CHAID analysis while making the findings more actionable for tutors, instructors, and student-support teams. The profiles should be interpreted as exploratory and interpretable representations of academic-risk patterns, rather than as fixed or deterministic student categories.

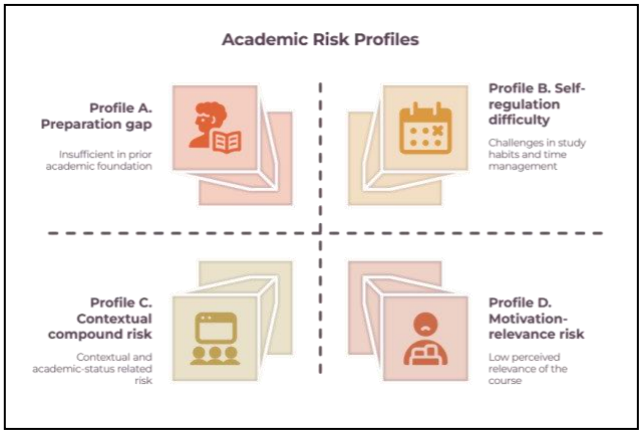


Fig. 2. Interpretable academic-risk profiles derived from explanatory and CHAID-based analysis.

Actionable Profile Summary

Table II translates the interpretable profiles into possible future support mechanisms. These actions are proposed as examples of how the profiles could inform AI-assisted or tutoring-oriented support. They were not implemented or evaluated in the present study.

These support mechanisms are proposed as future implementation options derived from the profiles; the present study did not implement or evaluate their effectiveness. In this sense, the study's contribution is not an operational AI system, but an interpretable empirical basis for designing future AI-assisted early-alert and academic-support strategies.

Table 2. Interpretable risk profiles and possible AI-assisted support

Risk profile	Main indicators	Possible AI-assisted / tutoring support
Preparation gap	Prior high-school average; perceived previous knowledge	Adaptive prerequisite review; subject-specialized chatbot tutor; targeted tutoring
Self-regulation difficulty	Homework completion; time management	Student-facing dashboard; SRL conversational agent; weekly study-plan nudges
Contextual compound risk	Scholarship context; academic status; cohort-related variation	Proactive advising; human-in-the-loop early alert; academic support referral
Motivation-relevance risk	Low perceived importance of physics	Career-linked examples; personalized feedback; chatbot-guided relevance prompts

Discussion

The results show that early academic performance in introductory physics courses was associated with a multidimensional set of variables rather than with a single isolated predictor. Prior academic preparation, perceived sufficiency of previous knowledge, academic status, study habits, sleep, time management, scholarship context, cohort-related variation, and perceived subject relevance were associated with early performance and informed the profiling process. This supports the view that early academic risk in first-year engineering education should be understood as the interaction of academic, behavioral, contextual, motivational, and well-being-related dimensions.

A key finding is the relevance of prior preparation. Students with lower high-school averages and those who reported insufficient previous knowledge obtained lower first-month grades. This suggests that early risk detection in foundational physics should include information about prerequisite knowledge and prior academic trajectories, not only current course performance. In practical terms, preparation-related indicators may help identify students who require diagnostic review, prerequisite reinforcement, or targeted tutoring before the course becomes more demanding.

The results also highlight the importance of self-regulation. Homework completion and time-management self-evaluation were associated with early academic performance. This finding points to a type of risk that may be addressed through structured academic support rather than only through content remediation. Students with self-regulation difficulties may benefit from study-planning tools, progress dashboards, weekly nudges, or conversational agents designed to support goal setting and reflection. This is consistent with recent work on AI-powered learning analytics dashboards, AI-supported learning tools, student-facing dashboards for self-regulated learning, and conversational agents for self-regulated learning in higher education, which emphasizes the need to connect analytics with feedback, monitoring, and learner agency [7], [8], [15], [16].

Well-being-related indicators also appeared in the explanatory and profiling process. Sleeping hours were associated with early grades, suggesting that academic risk may be linked to students' physical routines and capacity to sustain attention, study effort, and recovery. This does not imply a causal relationship. Rather, it reinforces the need to avoid purely academic interpretations of underperformance. For tutors and academic advisors, early-alert systems should support careful and human-centered conversations with students instead of automatically assigning deterministic risk labels.

The scholarship-related findings require particular caution. Scholarship context was retained in the explanatory model and showed differentiated descriptive patterns, but these patterns are institution-specific and may reflect selection effects, program conditions, or additional unmeasured factors. Therefore, scholarship context should not be used as a deterministic risk marker. Instead, it should be considered as one contextual signal within a broader human-in-the-loop advising process. This distinction matters for responsible learning analytics, especially when risk models include variables linked to student background or institutional status.

In response to RQ2, the CHAID-based synthesis contributes by translating statistical results into four interpretable academic-risk profiles: i) preparation gap, ii) self-regulation difficulty, iii) contextual compound risk, and iv) motivation-relevance risk. These profiles make the results more actionable for tutors and student-support teams. Two students with similar low grades may require different forms of support: one may need prerequisite reinforcement, while another may need time-management guidance, motivational support, or academic advising. This is the main value of interpretable profiling compared with opaque prediction: it supports differentiated action rather than a generic at-risk label.

The proposed profiles can also inform future AI-assisted academic support. Recent studies on explainable learning analytics, course-success prediction, AI-based learning tools, and AI-supported academic support suggest that educational AI should combine prediction, interpretability, feedback, and pedagogical action rather than rely only on model accuracy [8], [10]–[12]. In this context, the profiles identified in this study could inform a conceptual early-support framework that connects the data required for risk detection with interpretable profiling, traffic-light decision support, AI-assisted tutoring mechanisms, and human-in-the-loop academic governance.

Figure 3 presents a conceptual framework for translating interpretable academic-risk profiles into future AI-assisted support processes. The framework begins with multidimensional data inputs, including

academic preparation, self-regulation, well-being, contextual indicators, and motivation. These inputs are then processed through an interpretable risk-profiling layer informed by SEM-selected variables and CHAID-based profiles. The resulting profiles can support a traffic-light decision layer in which green indicates regular monitoring, amber indicates emerging risk, and red indicates priority support.

The framework also shows how traffic-light status could be connected to AI-assisted support mechanisms, such as adaptive prerequisite review, student-facing dashboards, subject-specialized chatbot tutoring, self-regulated learning conversational agents, and proactive advising prompts. However, these mechanisms should not operate as fully automated decision systems. The human-in-the-loop governance layer is therefore central to the framework, as tutors, advisors, and student-support teams would validate alerts, interpret student needs, refer students to appropriate support, and ensure ethical safeguards [17], [18].

Finally, the framework includes expected benefits and recalibration. Potential benefits include earlier support, differentiated intervention, and greater student agency. Recalibration emphasizes that academic-risk profiling should be dynamic rather than fixed: new grades, engagement data, and student feedback should update the profile and adjust the support provided. Therefore, Figure 3 should be interpreted as a design-oriented framework for future research and institutional experimentation, not as an implemented or evaluated AI system.

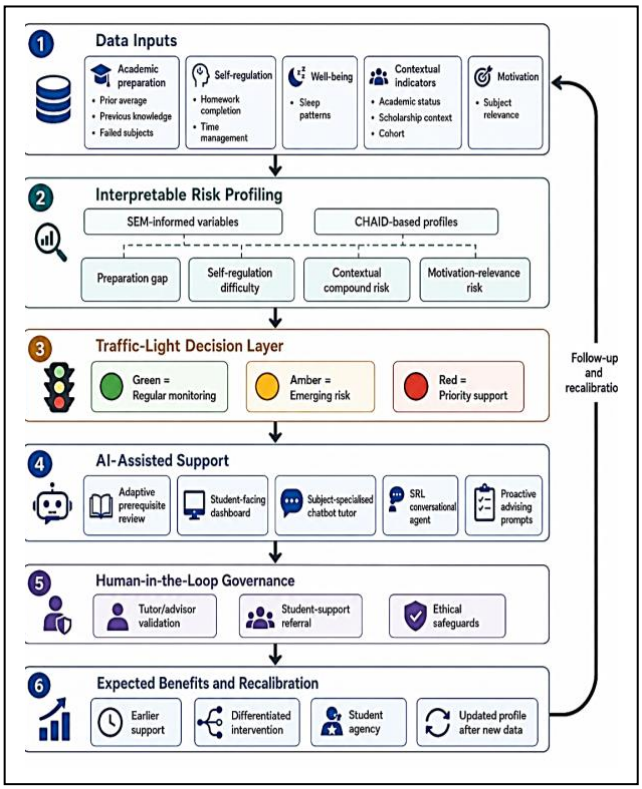


Fig. 3. Conceptual AI-assisted early-support framework derived from interpretable academic-risk profiles.

These tools are proposed only as future implementation options derived from the profiles; their effectiveness was not implemented or evaluated in the present study. Any future AI-assisted early-alert system based on these profiles should be validated with more recent cohorts, tested for fairness and calibration, and evaluated through implementation research before use in institutional decision-making [18].

Overall, this study's contribution is not the deployment of an AI system, but the development of an empirical and interpretable basis for future AI-assisted early support. By combining exploratory explanatory modeling and CHAID-based profiling, the study provides a transparent way to identify different types of academic vulnerability in first-year engineering students enrolled in introductory physics courses. This approach meets the need for learning analytics that are not only technically accurate but also understandable, actionable, and suitable for responsible educational decision-making.

Conclusions

This study examined how multidimensional student data can generate interpretable academic-risk profiles among first-year engineering students enrolled in introductory physics courses. In relation to RQ1, the results showed that early academic performance was associated with academic preparation, perceived sufficiency of previous knowledge, academic status, study habits, sleeping hours, time management, scholarship context, cohort-related variation, and perceived subject relevance. These findings reinforce the idea that early academic risk should not be interpreted as a single-variable problem, but as the interaction of academic, behavioral, contextual, motivational, and well-being-related dimensions.

In relation to RQ2, the study's main contribution is an interpretable academic-risk profiling approach that combines exploratory explanatory modeling with CHAID-based decision-tree analysis. The resulting profiles- preparation gap, self-regulation difficulty, contextual compound risk, and motivation-relevance risk- provide a transparent way to understand different forms of early academic vulnerability. This matters for tutors, instructors, and student-support teams because students with similar low grades may need different types of support.

The study also proposed a conceptual AI-assisted early-support framework based on the identified profiles. This framework links student indicators, interpretable risk dimensions, traffic-light decision support, AI-assisted support mechanisms, human-in-the-loop governance, and follow-up recalibration. However, the framework should be interpreted as a future design proposal rather than as an implemented or evaluated system. The study does not claim to have operationally deployed an AI-based early-warning system.

These findings should be interpreted in light of some methodological considerations. The dataset covers three pre-pandemic cohorts from 2017–2018 at a private

multi-campus university in Mexico, which may limit transferability to current cohorts and other institutional contexts. The study used observational and self-reported data and did not include fine-grained digital learning traces such as learning management system activity, submission patterns, or platform engagement. In addition, the authors used SEM as an exploratory explanatory procedure, and the CHAID profiles were not externally validated. Therefore, the profiles should not be interpreted as fixed student categories or as a fully deployable predictive model.

Future research should re-estimate and validate the profiles using more recent and diverse cohorts, integrate questionnaire-based indicators with behavioral learning analytics data, and compare alternative interpretable machine-learning methods. Further work should also evaluate calibration, fairness, privacy, transparency, and the educational effectiveness of AI-assisted support mechanisms such as dashboards, chatbot tutors, adaptive prerequisite review, self-regulated learning agents, and early human-in-the-loop alerts. In this way, interpretable academic-risk profiling can move from exploratory analysis toward responsible, evidence-based early support in first-year engineering education.

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