Estimating the Risk of Failing Physics Courses through the Monte Carlo Simulation

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***Abstract*—This research is conducted in the context of the Systems Engineering undergraduate program at the University of Córdoba in Colombia, aiming to calculate the risk of failing physics courses, which are considered particularly challenging for students. At this university, the academic semester is divided into three sessions, each equally weighted in the final grade. Our goal is to estimate the failure risk based on student performance in the earlier sessions. To this end, we collected a dataset comprising the session grades and final results of students enrolled in Physics I, II, and III during 2024. We then implemented a Monte Carlo simulation to calculate the absolute and relative risk of course failure. The results show that failing early sessions is strongly associated with a higher probability of failing the course, especially in Physics I and III. These insights can support lecturers in adjusting the syllabus and designing interventions to reduce dropout rates and improve student outcomes.**

***Keywords*-Monte Carlo simulation; educational innovation; computational social science.**

I. Introduction

Nowadays, academic success is a primary concern for universities worldwide. As a consequence, identifying strategies and conducting research to predict the risk of academic failure has become an active area of study within social computing, particularly through educational data mining approaches. These methods are commonly used to predict student dropout, delayed graduation [1]–[3], and the likelihood of course failure or withdrawal [4]–[13].

Our research focuses on the academic context of the University of Córdoba in Colombia, where each academic semester is split into three sessions, each lasting six weeks and contributing equally to the final grade. The final course grade is calculated as the mean of the student's grades across the three sessions. Within each session, no single assessment can exceed 40% of the session grade, meaning that each student undergoes at least nine evaluations during a semester.

This structure is designed to achieve several pedagogical goals: reducing the pressure of final exams, diversifying assessment strategies, encouraging consistent study habits, enabling continuous monitoring of learning progress, facilitating early interventions, and providing timely support to students. This approach is supported by several educational theories and instructional strategies, including constructivism, formative assessment, multiple intelligences theory, cognitive load theory, active learning, and outcome-based education.

According to constructivist theory, students build their understanding through interaction with their environment. Frequent evaluations help instructors monitor this evolving understanding and adjust teaching strategies accordingly.

Formative assessment emphasizes the use of ongoing evaluations throughout the instructional period to monitor learning, identify challenges, and guide teaching. This method offers continuous feedback to both students and instructors, aligning well with the university's evaluation strategy.

The theory of multiple intelligences posits that students possess diverse talents and learning preferences. A variety of assessments throughout the semester provides a more inclusive way to evaluate these varied strengths.

Cognitive load theory suggests that students learn more effectively when information is presented in manageable segments. Multiple evaluations distributed over time align with this principle by reducing cognitive overload.

Active learning promotes student engagement through problem-solving, discussions, and hands-on activities. Multiple evaluations throughout the semester can reinforce this approach by encouraging students to actively engage with the material.

At the University of Córdoba, Outcome-Based Education (OBE) is the foundational approach. It emphasizes clearly defined learning outcomes and assessments aligned with those outcomes. Dividing the semester into multiple sessions allows for a more granular alignment of evaluations with specific goals.

The university's OBE model is integrated with the Structure of the Observed Learning Outcomes (SOLO) taxonomy, which categorizes learning into five levels:

1) Prestructural (0.0–2.0): The student has not yet grasped the key concepts.
2) Unistructural (2.1–2.9): The student understands a single aspect of the task.
3) Multistructural (3.0–3.7): The student understands several aspects, but without integration.
4) Relational (3.8–4.5): The student can integrate multiple aspects meaningfully.
5) Extended Abstract (4.6–5.0): The student demonstrates deep understanding and applies concepts to new contexts.

To pass an evaluation, a student must achieve at least the multistructural level, corresponding to a grade above 3.0.

By structuring learning outcomes around SOLO taxonomy principles, the curriculum offers a coherent and progressively challenging learning experience. This structure emphasizes the development of deeper understanding as students progress. However, despite this pedagogical framework, physics courses remain particularly challenging for systems engineering students, who often struggle to reach the relational or extended abstract levels. For example, in 2024, the average final grades for Physics I, II, and III were 3.17, 3.30, and 3.35, respectively, suggesting limited integration of concepts or application to real-world contexts.

In an endeavor to mitigate failure and dropout, the university assumes students at risk of failing a course if they fail either of the first two sessions. This leads us to pose the following research questions:

- What is the risk of failing a physics course if a student fails the first session?
- What is the risk if a student fails the second session but passed the first?
- What is the risk if a student fails both the first and second sessions?

To the best of our knowledge, no prior research has directly addressed these questions. To fill this gap, we simulate all possible grade scenarios using the Monte Carlo numerical method, informed by historical academic performance data. This method has been used in similar educational contexts, for instance, to evaluate curriculum effectiveness [14] or to estimate students' motivation in learning scientific computing [15].

Our simulations reveal the following findings:

- For Physics I, approximately 42 out of 100 students are at risk of failing if they failed the first session; 44 out of 100 if they failed the second session; and 63 out of 100 if they failed both.
- For Physics II, about 28 out of 100 students are at risk if they failed the first session; 14 out of 100 if they failed the second; and 49 out of 100 if both were failed.
- For Physics III, around 49 out of 100 students are at risk if they failed the first session; 11 out of 100 if they failed the second; and 14 out of 100 if they failed both.

These insights contribute to implement early intervention strategies and improve academic support in physics courses.

Finally, the rest of this article is outlined as follows: in Section II, we present the research and simulation methodology adopted in this research, while we present and discuss the results in Section II. The article concludes in Section IV.

II. Research Methodology

We adopted a quantitative approach, collecting the session and final grades of 100 students enrolled in physics courses at the University of Córdoba in 2024. Specifically, 36 students were enrolled in Physics I, 32 in Physics II, and 32 in Physics III. The relatively small dataset size reflects the recent implementation of the previously described Outcome-Based Education (OBE) framework at the institution.

Given the limited number of students and the sparsity of failure cases in certain session combinations (as shown in Table I), direct estimation of absolute and relative risks from empirical data would be statistically unreliable. For example, the dataset contains no instances of students failing the Physics I course after failing the second or third session, provided they passed the first. This type of data sparsity presents a challenge for risk estimation.

TABLE I. Number of students who failed a physics when they have failed at least one session (S1, S2, and S3).

Course	Failed S1	Failed S2	Failed S3	Failed Students
Physics 1	Yes	Yes	Yes	1
	Yes	Yes	No	7
	Yes	No	No	2
	No	Yes	Yes	0
	No	Yes	No	0
Physics 2	Yes	Yes	Yes	2
	Yes	Yes	No	3
	Yes	No	No	0
	No	Yes	Yes	0
	No	Yes	No	0
Physics 3	Yes	Yes	Yes	0
	Yes	Yes	No	1
	Yes	No	No	0
	No	Yes	Yes	0
	No	Yes	No	0

To address this, we employed the Monte Carlo simulation method [16] to explore the full probability space of possible student performance outcomes. Instead of relying solely on the small number of observed cases, we reconstructed the grade distribution using a parametric model, specifically, a normal distribution, with parameters (mean and standard deviation) derived from the original dataset. Grades were clipped to fall within the [0, 5] scale, as the normal distribution might otherwise generate implausible values in the tails. This allowed us to simulate large numbers of plausible student grade combinations and estimate the associated risks under uncertainty.

In essence, the Monte Carlo simulation serves as a data-informed method for approximating risk in underrepresented or unobserved configurations, enabling generalization beyond the empirical observations while remaining grounded in the observed statistical characteristics of the data.

Thus, the probability that a student fails a physics course given that they failed the jth session is denoted as $P(y < 3 \mid x_j < 3)$, where y is the final course grade. A final grade below 3.0 indicates course failure, as previously explained. The variable x_j represents the grade the student obtained in the jth session, with $j = 1, 2, 3$. Thus, $x \in \mathcal{X} \subseteq [0, 5]^3$ is a real-valued three-dimensional vector containing the grades from each session, all within the range [0, 5]. A session grade below 3.0 ($x_j < 3$) indicates failure in that session.

Since the final grade y is the arithmetic mean of the three session grades, it is computed as:

$$y = \frac{1}{3} \sum_{j=1}^{3} x_j \tag{1}$$

The *Absolute Risk (AR)* of failing the course given failure in session jth is defined as:

$$AR(y < 3 \mid x_j < 3) = \int_{\mathcal{X}} \frac{P(y < 3, x_j < 3)}{P(x_j < 3)}\, dx \quad (2)$$

Similarly, the absolute risk of failing the course given that the student did *not* fail session jth is:

$$AR(y < 3 \mid x_j \geq 3) = \int_{\mathcal{X}} \frac{P(y < 3, x_j \geq 3)}{P(x_j \geq 3)}\, dx \quad (3)$$

The *Relative Risk (RR)* is defined as the ratio of these two quantities:

$$RR(y < 3 \mid x_j < 3) = \frac{AR(y < 3 \mid x_j < 3)}{AR(y < 3 \mid x_j \geq 3)} \quad (4)$$

To estimate these quantities via the Monte Carlo method, we generate an $N \times 3$-dimensional matrix $X \in [0,5]^{N\times 3}$, where its component $X_{ij} \sim \mathcal{N}(\mu_j, \sigma_j)$ is normally distributed with mean μ_j and standard deviation σ_j computed from the historical grades of students in session j of each physics course.

The absolute risk $AR(y < 3 \mid x_j < 3)$ is approximated as:

$$AR(y < 3 \mid x_j < 3) \approx \frac{\sum_{i=1}^{N} \mathbf{1}(y_i < 3 \wedge X_{ij} < 3)}{\sum_{i=1}^{N} \mathbf{1}(X_{ij} < 3)} \quad (5)$$

where $\mathbf{1}(u) = 1$ if the condition u is true, and 0 otherwise. Similarly, the absolute risk for students who did *not* fail session j is:

$$AR(y < 3 \mid x_j \geq 3) \approx \frac{\sum_{i=1}^{N} \mathbf{1}(y_i < 3 \wedge X_{ij} \geq 3)}{\sum_{i=1}^{N} \mathbf{1}(X_{ij} \geq 3)} \quad (6)$$

Finally, the relative risk is calculated as:

$$RR(y < 3 \mid x_j < 3) \approx \frac{\frac{\sum_{i=1}^{N} \mathbf{1}(y_i<3 \wedge X_{ij}<3)}{\sum_{i=1}^{N} \mathbf{1}(X_{ij}<3)}}{\frac{\sum_{i=1}^{N} \mathbf{1}(y_i<3 \wedge X_{ij}\geq 3)}{\sum_{i=1}^{N} \mathbf{1}(X_{ij}\geq 3)}} \quad (7)$$

This simulation-based approach enables us to estimate the conditional risks associated with failing individual sessions and provides a probabilistic understanding of academic outcomes based on partial performance.

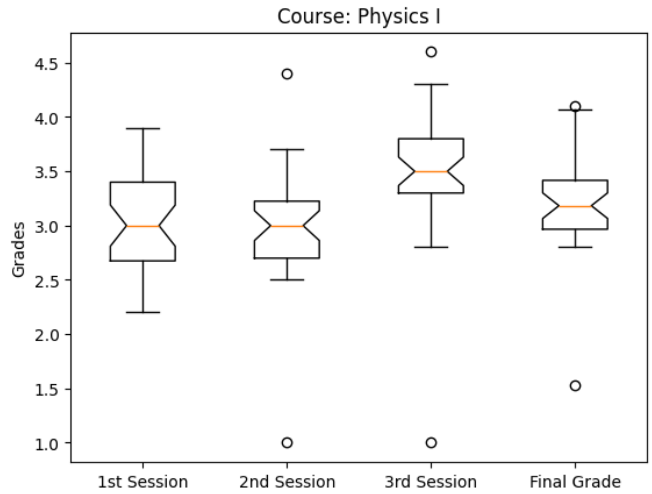

Figure 1. Grades of the students enrolled in the physics I course in 2024

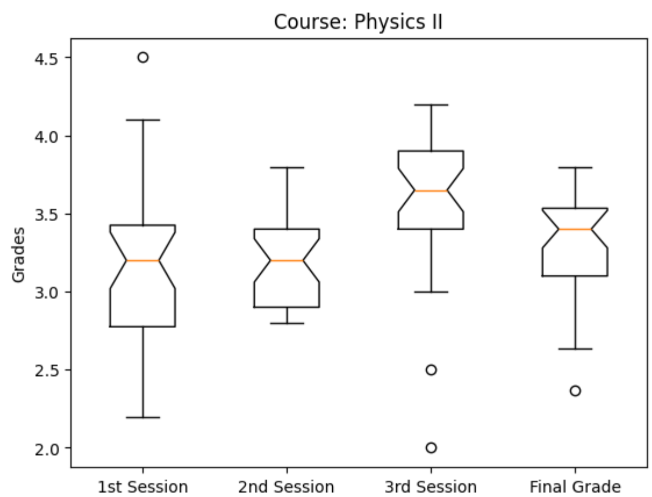

Figure 2. Grades of the students enrolled in the physics II course in 2024

The simulation was implemented in Python using the NumPy and Matplotlib libraries. The anonymized dataset and corresponding source code are available upon request from the first author.

III. THE RESEARCH RESULTS AND DISCUSSION

Based on the collected dataset, the mean grades for the first, second, and third sessions in the Physics I course were 3.03, 2.98, and 3.50, respectively, with corresponding standard deviations of 0.43, 0.53, and 0.58. As shown in Figure 1, the box plot corresponding to the final grade illustrates that students rarely failed the course outright or achieved exceptionally high grades. Furthermore, there appears to be a general trend of improved performance in the final session.

Similarly, the mean grades for Physics II were 3.17, 3.20, and 3.55 for the first, second, and third sessions, respectively, with standard deviations of 0.57, 0.27, and 0.47. Figure 2 demonstrates a performance pattern comparable to Physics I,

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where both failures and outstanding performances were infrequent. However, a notable difference emerges in the second session: while performance in Physics I declined slightly from 3.03 to 2.98, Physics II showed a slight improvement, with the average grade increasing from 3.17 to 3.20. This suggests a possible difference in instructional design or assessment difficulty between the two courses during that session.

Additionally, the dataset reveals that the mean grades for the first, second, and third sessions in the Physics III course are 3.12, 3.28, and 3.66, respectively, with standard deviations of 0.41, 0.36, and 0.31. Figure 3 illustrates that student grades in this course follow a pattern similar to the previous two physics courses.

TABLE II. EXPECTED FINAL GRADES BY COURSE OBTAINED FROM THE MONTE CARLO SIMULATION RESULTS.

Course	Expected Grade	Standard Error	95% CI
Physics 1	3.178	1.2×10^{-4}	[3.178, 3.179]
Physics 2	3.305	10^{-4}	[3.30498, 3.305]
Physics 3	3.354	1.1×10^{-4}	[3.353, 3.354]

The results of the numerical simulation show that the expected final grades for Physics I, II, and III are 3.17, 3.31, and 3.35, respectively (see Table II). Figures 4–6 demonstrate how the Monte Carlo simulations converge to these values, which are consistent with the histograms presented in Figures 7–9, displaying the distribution of the final grades for each course.

TABLE III. ABSOLUTE AND RELATIVE RISK BY SESSION AND COURSE.

Course	Session(s) Failed	Absolute Risk (%)	Relative Risk (%)	95% CI (RR)
Physics I	S1	41.66	2.77	[2.762, 2.777]
	S2	43.52	4.05	[4.032, 4.059]
	S1 and S2	62.93	4.18	[4.172, 4.195]
Physics II	S1	28.11	12.62	[12.532, 12.703]
	S2	22.76	2.49	[2.484, 2.505]
	S1 and S2	49.03	22.00	[21.851, 22.159]
Physics III	S1	10.61	17.93	[17.601, 18.267]
	S2	14.30	8.11	[8.021, 8.196]
	S1 and S2	33.05	55.86	[54.827, 56.913]

A summary of the relative and absolute risk estimates derived from the Monte Carlo simulation is presented in Table III. The corresponding relative risks for each course are depicted using forest plots in Figures 10–12. As expected, failing the first two sessions corresponds to the highest relative risk of failing a physics course. It is noteworthy that for Physics I, failing the second session alone is associated with a higher relative risk than failing the first session. This pattern differs from Physics II and III, where failing the first session presents a greater relative risk. Notably, the risk of failing Physics I after failing only the second session is nearly equivalent to the risk of failing after both the first and second sessions.

The absolute risk of course failure among students exposed to session failures versus those unexposed is compared in Table IV. The results of the simulation reveal that there is an absolute risk of 41.66% that students fail the Physics I course if they fail the first session. This corresponds to a risk difference

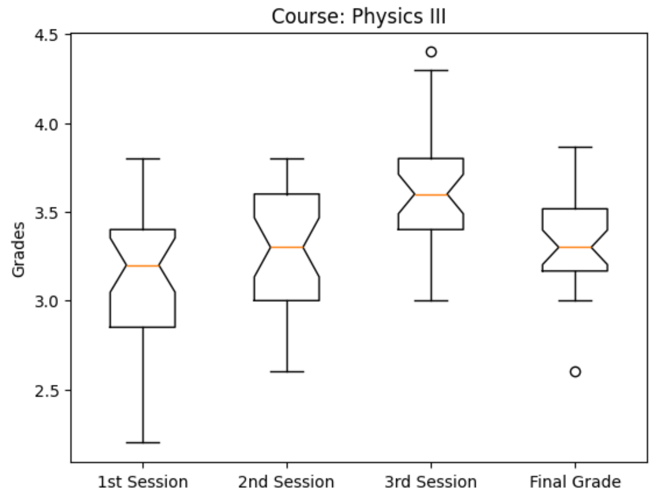

Figure 3. Grades of the students enrolled in the physics III course in 2024

of 26.62 percentage points, with a 95% confidence interval of [26.554%, 26.688%], compared to an absolute risk of 15.04% for students who do not fail the first session. This difference is statistically significant, indicating a meaningful association between failing the first session and ultimately failing Physics I. Furthermore, the relative risk is 2.77, suggesting that students who fail the first session are 2.77 times more likely to fail the course than those who do not (see Figure 10).

TABLE IV. COMPARISON OF ABSOLUTE RISK (AR) OF COURSE FAILURE BETWEEN STUDENTS EXPOSED AND UNEXPOSED TO FAILING PREVIOUS SESSIONS, WITH CORRESPONDING RISK DIFFERENCES (RD)

Course	Session(s) Failed	AR (%) exposed	AR (%) unexposed	RD (%)	95% CI (RD)
Physics I	S1	41.66	15.66	26.62†	[26.554, 26.688]
	S2	43.52	10.76	32.76†	[32.696, 32.823]
	S1 and S2	62.93	15.04	47.89†	[47.805, 47.975]
Physics II	S1	28.11	2.23	25.89†	[25.829, 25.944]
	S2	22.76	9.12	13.63†	[13.563, 13.707]
	S1 and S2	49.03	2.23	46.80†	[46.673, 46.934]
Physics III	S1	10.61	0.59	10.02†	[9.961, 10.071]
	S2	14.30	1.76	12.54†	[12.455, 12.623]
	S1 and S2	33.05	0.59	32.45†	[32.276, 32.634]

† (p-value < 0.05)

The absolute risk of failing the Physics I course increases to 43.52% if students fail the second session. In this case, the risk difference is 32.76 percentage points, with a 95% confidence interval of [32.696%, 32.823%], compared to an absolute risk of 10.76% among students who pass the second session. The relative risk in this scenario is 4.05, indicating that students who fail the second session are over four times more likely to fail the course than those who succeed (see Figure 10).

When students fail both the first and second sessions of Physics I, the absolute risk of failing the course increases to 62.93%. The associated risk difference is 47.89 percentage points, with a 95% confidence interval of [47.805%, 47.975%], compared to the 15.04% absolute risk observed among those who do not fail the first two sessions. The relative risk of 4.18 further highlights the increased likelihood of course failure under these conditions (see Figure 10).

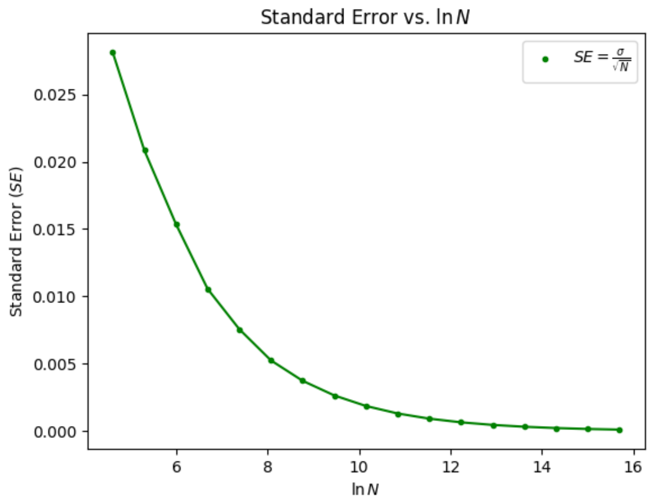

Figure 4. The simulation converges to the expected final grade of 3.178 in the Physics I course as $N = 6,553,600$, with a standard error of 1.2×10^{-4}. The result lies within the 95% confidence interval of [3.178, 3.179].

Regarding the Physics II course, the simulation shows that students who fail the first session have an absolute risk of 28.11% of failing the course. This results in a risk difference of 25.89 percentage points, with a 95% confidence interval of [25.829%, 25.944%], compared to an absolute risk of just 2.23% for those who do not fail the first session. The relative risk of 12.62 indicates that students who fail the first session are over 12 times more likely to fail Physics II (see Figure 11).

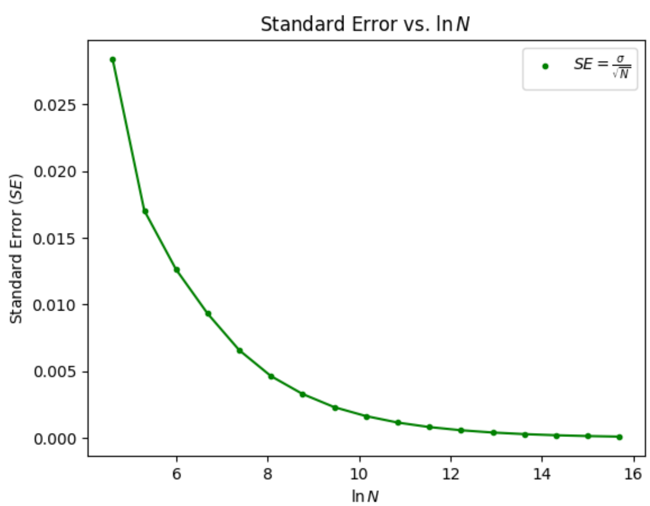

Figure 5. The simulation convergences to the expected final grade of 3.305 in the Physics II course as $N = 6,553,600$, with a standard error of 10^{-4}. The result lies within the 95% confidence interval of [3.30498, 3.305].

Failing the second session in Physics II results in an absolute risk of 22.76%, with a risk difference of 13.63 percentage points and a 95% confidence interval of [13.563%, 13.707%], compared to an absolute risk of 9.12% for those who do not fail the second session. The relative risk of 2.49 indicates a significantly increased likelihood of failing the course for these students (see Figure 11).

When students fail both the first and second sessions in Physics II, the absolute risk of failing the course rises sharply to 49.03%. This is associated with a risk difference of 46.80 percentage points and a 95% confidence interval of [46.673%, 46.934%], compared to the same 2.23% absolute risk for students who succeed in both sessions. The relative risk of 22 underscores the very strong association between poor performance in the initial sessions and course failure (see Figure 11).

In the case of Physics III, students who fail the first session have an absolute risk of 10.61% of failing the course. The risk difference in this case is 10.02 percentage points, with a 95% confidence interval of [9.961%, 10.071%], compared to an absolute risk of 0.59% among students who pass the first session. The relative risk is 17.93, indicating a very strong link between failing the first session and failing the course (see Figure 12).

For students who fail the second session in Physics III, the absolute risk of course failure is 14.30%, compared to 1.76% among those who pass that session. This results in a risk difference of 12.54 percentage points, with a 95% confidence interval of [12.455%, 12.623%].The corresponding relative risk of 8.11 suggests that failing the second session in Physics III is associated with a higher likelihood of course failure than the same condition in Physics I and II (see Figure 12).

Finally, for students who fail both the first and second sessions in Physics III, the absolute risk of failing the course increases to 33.05%. The risk difference is 32.45 percentage points, with a 95% confidence interval of [32.276%, 32.634%], in contrast to the absolute risk of 0.59% for students who succeed in both sessions. The relative risk of 55.86 implies an exceptionally high likelihood of failure under these circumstances (see Figure 12).

IV. Conclusion and Perspective

We adopted Monte Carlo simulation because the collected dataset is small and statistically unstable or undefined (i.e., division by zero or nearly zero) to estimate absolute and relative risk causing even high variance. Thereby the Monte Carlo method provides a data-informed but smoothed approximation of what outcomes would look like using a larger dataset with similar distributional properties of the collected dataset.

We draw the following conclusions from the results:

- Teaching staff and lecturers may consider reorganizing the syllabus to reduce the risk of course failure by incorporating the observed probabilities of failure at each session.
- In Physics II and III, failing the first session is associated with a higher risk of overall course failure than failing the second session. This pattern might be driven by psychological or motivational factors; students who begin the course with poor performance often experience discouragement, reduced engagement, and diminished resilience in response

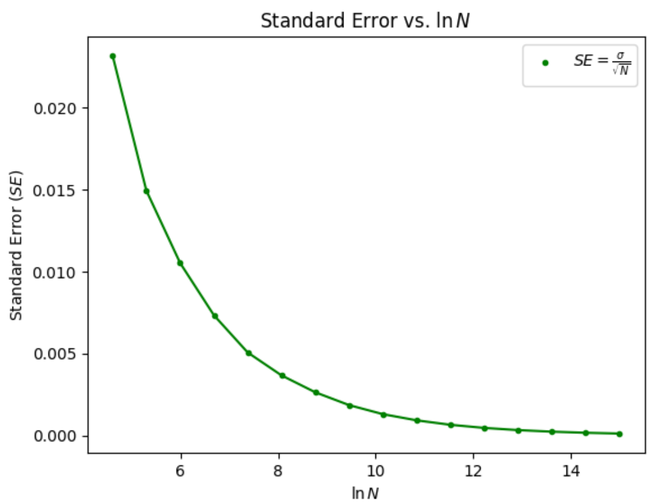

Figure 6. The simulation convergences to the expected final grade of 3.354 in the Physics III course as $N = 3,276,800$, with a standard error of 1.1×10^{-4}. The result lies within the 95% confidence interval of [3.353, 3.354].

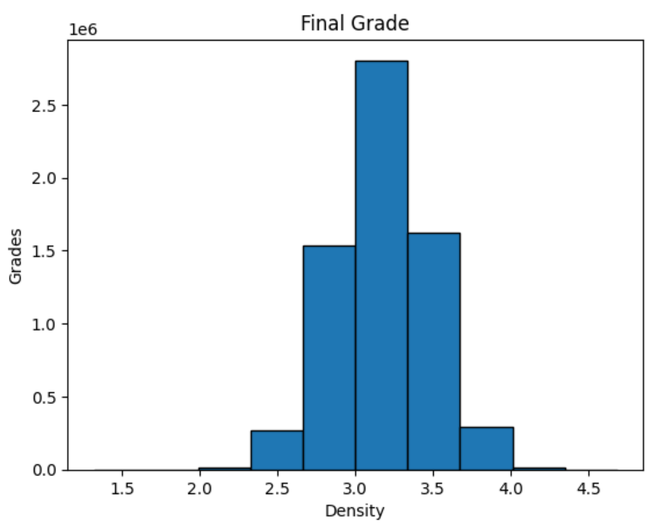

Figure 7. Distribution of final grades obtained from the simulation for the Physics I course.

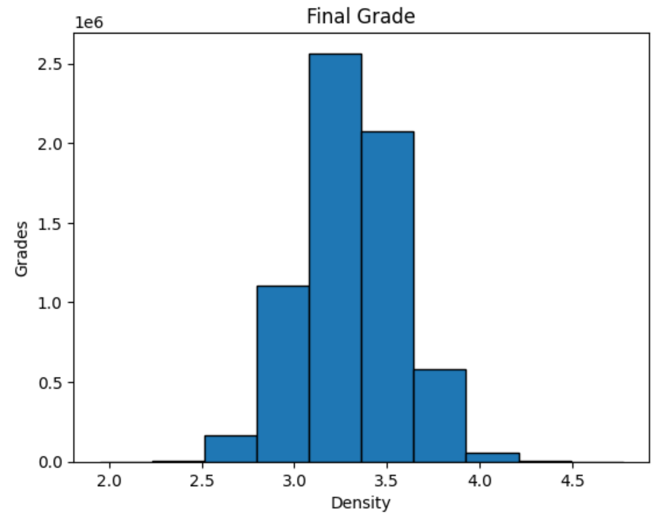

Figure 8. Distribution of final grades obtained from the simulation for the Physics II course.

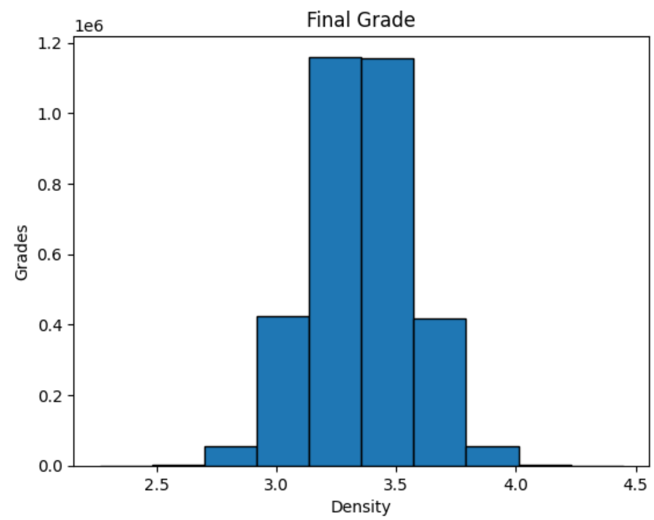

Figure 9. Distribution of final grades obtained from the simulation for the Physics III course.

to subsequent academic challenges [17], [18]. More broadly, performance in the first or second session is strongly associated with final course outcomes. Beyond mere statistical correlation, early academic struggles may serve as indicators of underlying motivational or behavioral challenges, making them valuable triggers for early intervention and academic support strategies. Further research is needed to design and implement targeted measures that might help students recover from early setbacks and improve their overall performance trajectory.

- In Physics III, students who pass the first two sessions have an almost negligible risk of failing the course. Consequently, they may become complacent and neglect the final session. In contrast, students who fail the first two sessions face a significantly high risk of failing the course. This discrepancy suggests an imbalance in the difficulty and weight of the course sessions. Simulating alternative scenarios may help to redesign the course structure and improve student success rates.
- A consistent trend of improved student performance is observed from Physics I to Physics III, as indicated by higher average grades and lower absolute risk in the later courses. This pattern might reflect students' adaptation to course demands or the development of stronger academic skills over time. Nevertheless, in the Systems Engineering program, students are not strictly required to follow prerequisite sequencing. For instance, a student may enroll in Physics III without having previously taken Physics I or II. Although most students typically follow the intended

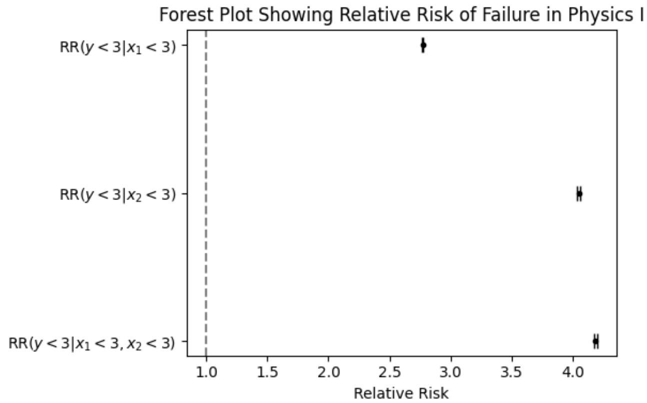

Figure 10. Forest plot showing the relative risk (RR) of failing the Physics I course. $RR(y < 3 \mid x_1 < 3) = 2.77$, with a 95% confidence interval of [2.762, 2.777]; $RR(y < 3 \mid x_2 < 3) = 4.05$, with a 95% confidence interval of [4.032, 4.059]; and $RR(y < 3 \mid x_3 < 3) = 4.18$, with a 95% confidence interval of [4.172, 4.195]. In all cases, the Wald test p-value is less than 0.05.

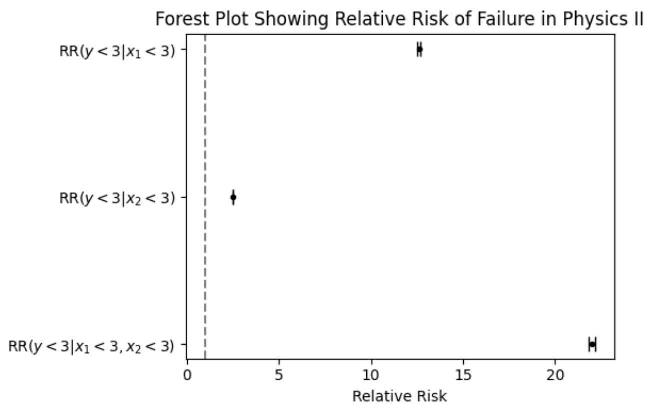

Figure 11. Forest plot showing the relative risk (RR) of failing the Physics II course. $RR(y < 3 \mid x_1 < 3) = 12.62$, with a 95% confidence interval of [12.532, 12.703]; $RR(y < 3 \mid x_2 < 3) = 2.49$, with a 95% confidence interval of [2.484, 2.505]; and $RR(y < 3 \mid x_3 < 3) = 22$, with a 95% confidence interval of [21.851, 22.159]. In all cases, the Wald test p-value is less than 0.05.

curricular progression, exceptions do occur. In this study, information about such cases was not available.

- The simulation based on the Monte Carlo numerical method has proven to be a valuable tool for estimating the absolute and relative risks of course failure. It might support evidence-based decision-making in academic planning and policy design. Grades were simulated using a normal distribution, with parameters estimated from observed student data. While our dataset includes relatively few course failures, we modeled grades probabilistically to reflect the empirical distribution, ensuring that rare but plausible outcomes (e.g., failing scenarios) were represented.

As directions for further research, we propose the following:

- We shall collect additional data to apply this methodology to other courses and broaden the scope of academic risk analysis.

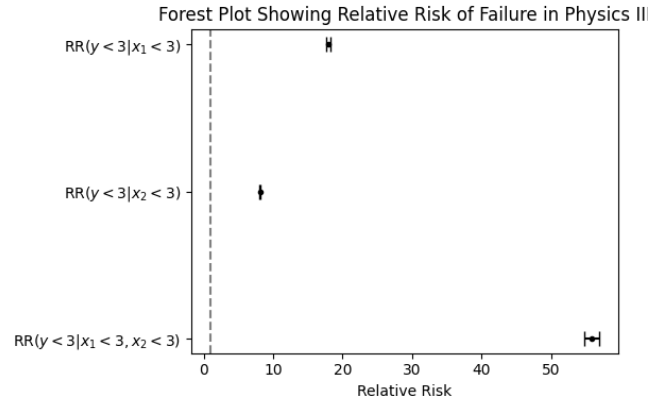

Figure 12. Forest plot showing the relative risk (RR) of failing the Physics III course. $RR(y < 3 \mid x_1 < 3) = 17.93$, with a 95% confidence interval of [17.601, 18.267]; $RR(y < 3 \mid x_2 < 3) = 8.11$, with a 95% confidence interval of [8.021, 8.196]; and $RR(y < 3 \mid x_3 < 3) = 55.86$, with a 95% confidence interval of [54.827, 56.913]. In all cases, the Wald test p-value is less than 0.05.

- We shall extend the simulation to incorporate the specific coursework or evaluation structure assigned in each session, aiming to estimate risk with greater accuracy.
- We shall adapt the simulation to assume an non-uniform weighting of sessions when calculating final grades, in order to reduce the risk of failure.
- We shall incorporate bootstrap resampling to estimate the variability of simulation parameters (i.e., mean and standard deviation) in order to strengthening the robustness of the risk estimates under data scarcity.

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