UNIVERSIDAD DE CÓRDOBA

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

Isaac Caicedo-Castro, Rubby Castro-Púche, and Samir Castaño-Rivera

IARIA

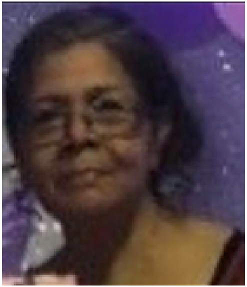
GPTMB 2025

**University of Córdoba in Colombia: Striving for Quality, Innovation, and Inclusivity to Transform Our Region.**

# Who am I?

- Isaac Caicedo-Castro
- Full Professor in the Department of Systems Engineering at the University of Córdoba in Colombia
- Ph.D. in Informatics - University of Grenoble Alpes in France
- Ph.D. in Systems and Computing Engineering - National University of Colombia
- Corresponding author: **isacaic@correo.unicordoba.edu.co**

# My team mates 1/2



- Rubby Castro-Púche
- Full Professor in the Department of Social Science at the University of Córdoba in Colombia
- M.Sc. in Education - La Salle University in Colombia

# My team mates 2/2

- Samir Castaño-Rivera
- Head of the Systems Engineering Department at the University of Córdoba in Colombia
- M.Sc. in Free Software - Autonomous University of Bucaramanga in Colombia

# Agenda

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# Introduction

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Prediction student dropout, delayed graduation [da Silva et al., 2022, Caicedo-Castro et al., 2022, Zihan et al., 2023]

# Introduction


Likelihood of course failure or withdrawal
[Lykourentzou et al., 2009, Kabathova and Drlik, 2021, Niyogisubizo et al., 2022, Čotić Poturić et al., 2022b, Čotić Poturić et al., 2022a, Caicedo-Castro et al., 2023b, Caicedo-Castro et al., 2023a, Caicedo-Castro, 2023, Caicedo-Castro, 2024b, Caicedo-Castro, 2024a]

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- No single assessment can exceed 40% of the session grade $\implies$ at least nine evaluations during a semester

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- Providing timely support to students.

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To pass an evaluation, a student must achieve at least the multistructural level

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- Evaluate curriculum effectiveness [Torres et al., 2021]

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- Evaluate curriculum effectiveness [Torres et al., 2021]
- Estimate students' motivation in learning scientific computing [Caicedo-Castro et al., 2025].

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# Research Methodology

- Quantitative approach

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- Session 'n' final grades $\rightarrow$ 100 students $\rightarrow$ physics courses
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- Recent implementation $\rightarrow$ Outcome-Based Education (OBE) framework
- Limited number of students $\implies$ sparsity of failure cases in certain session combinations

# Research Methodology

Number of students who failed Physics 1 course when they have failed at least one session (S1, S2, and S3).

| **Failed S1** | **Failed S2** | **Failed S3** | **Failed Students** |
|---|---|---|---|
| Yes | Yes | Yes | 1 |
| Yes | Yes | No | 7 |
| Yes | No | No | 2 |
| No | Yes | Yes | 0 |
| No | Yes | No | 0 |

# Research Methodology

Number of students who failed Physics 2 course when they have failed at least one session (S1, S2, and S3).

| **Failed S1** | **Failed S2** | **Failed S3** | **Failed Students** |
|---|---|---|---|
| Yes | Yes | Yes | 2 |
| Yes | Yes | No | 3 |
| Yes | No | No | 0 |
| No | Yes | Yes | 0 |
| No | Yes | No | 0 |

# Research Methodology

Number of students who failed Physics 3 course when they have failed at least one session (S1, S2, and S3).

| **Failed S1** | **Failed S2** | **Failed S3** | **Failed Students** |
|---|---|---|---|
| Yes | Yes | Yes | 0 |
| Yes | Yes | No | 1 |
| Yes | No | No | 0 |
| No | Yes | Yes | 0 |
| No | Yes | No | 0 |

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- full probability space of possible student performance outcomes
- the small number of observed cases
- Normal distribution: (mean and standard deviation) $\rightarrow$ original dataset
- Grades were clipped to fall within the [0, 5] scale

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

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- 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.

# Agenda

Introduction

Research Methodology

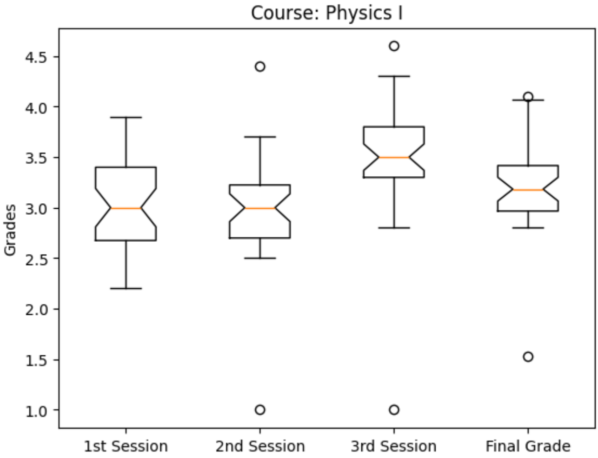
The Research Results and Discussion

Conclusion and Perspectives

Question and Answer Session

# The Research Results and Discussion

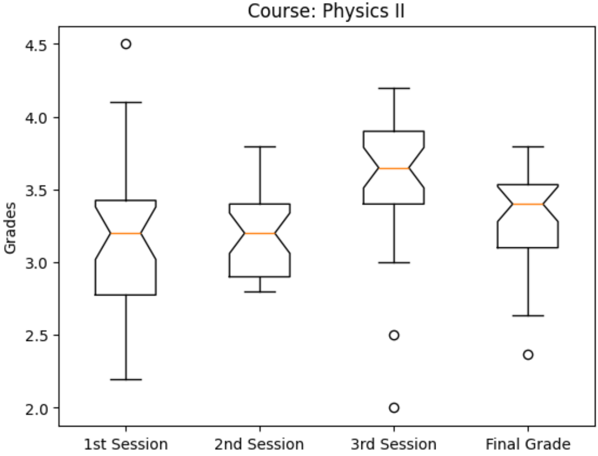
Physics I: $\mu_1 = 3.03$, $\mu_2 = 2.98$, and $\mu_3 = 3.50$; $\sigma_1 = 0.43$, $\sigma_2 = 0.53$, and $\sigma_3 = 0.58$




Grades of the students enrolled in the physics I course

# The Research Results and Discussion

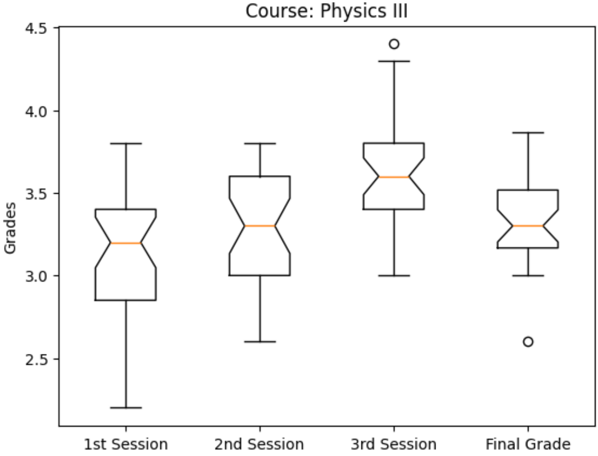
Physics II: $\mu_1 = 3.17$, $\mu_2 = 3.20$, and $\mu_3 = 3.55$;
$\sigma_1 = 0.57$, $\sigma_2 = 0.27$, and $\sigma_3 = 0.47$




Grades of the students enrolled in the physics II course

# The Research Results and Discussion

Physics III: $\mu_1 = 3.12$, $\mu_2 = 3.28$, and $\mu_3 = 3.66$;
$\sigma_1 = 0.41$, $\sigma_2 = 0.36$, and $\sigma_3 = 0.31$

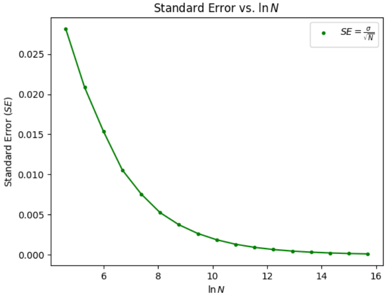



Grades of the students enrolled in the physics III course

# The Research Results and Discussion

## Expected Final Grades by Course Obtained from the Monte Carlo Simulation Results

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




$N = 6,553,600$

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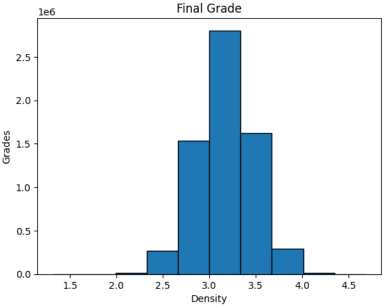


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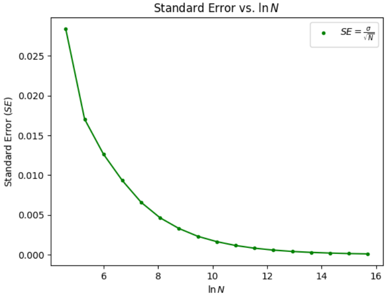


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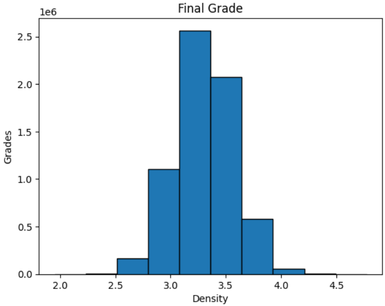


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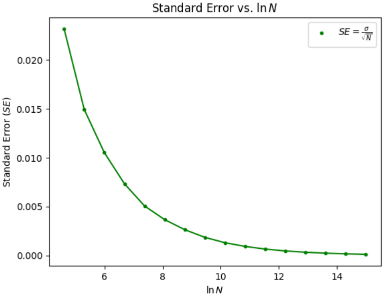


$N = 3,276,800$

# The Research Results and Discussion

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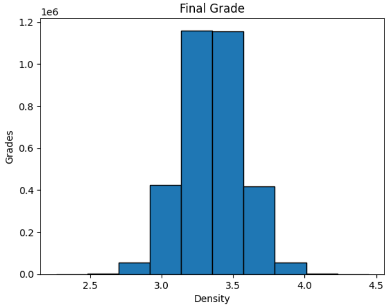



$N = 3,276,800$

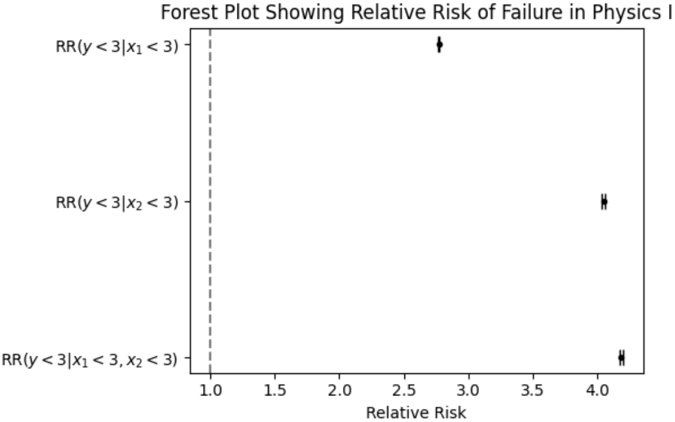
# The Research Results and Discussion

## Absolute and Relative Risk by Session and Course

| **Course** | **Session(s) Failed** | **AR** (%) | **RR** (%) | **95% CI (RR)** |
|---|---|---|---|---|
| Phy 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] |
| Phy 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] |
| Phy 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] |

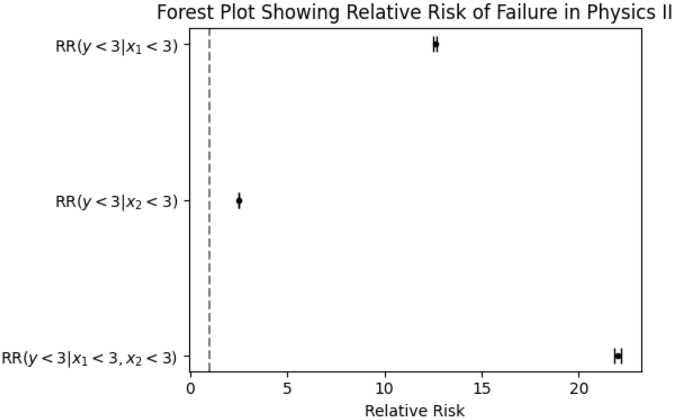
# The Research Results and Discussion

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



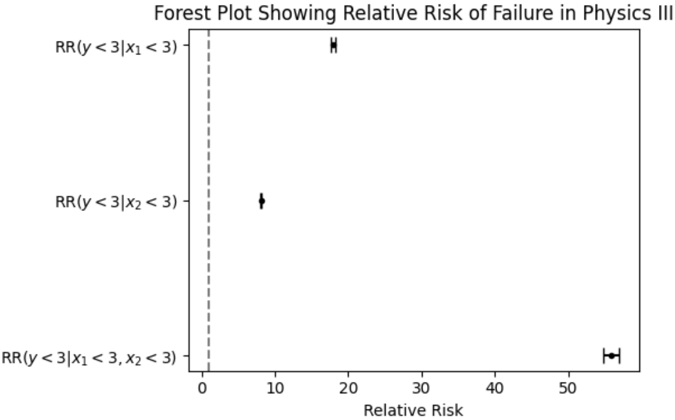
# The Research Results and Discussion

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



# The Research Results and Discussion

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



# The Research Results and Discussion

## Comparison of AR of Course Failure Between Students Exposed and Unexposed to Failing Previous Sessions, with Corresponding RD

| **Crs.** | **Sess.(s) Failed** | **AR** (%) **exposed** | **AR** (%) **unexposed** | **RD** (%) | **95% CI (RD)** |
|---|---|---|---|---|---|
| Phy 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] |
| Phy 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] |
| Phy 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 $< 0.05$)

# Agenda

# Conclusions

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- Improved student performance is observed from Physics I to Physics III
- Simulation based on the Monte Carlo numerical method $\rightarrow$ Support evidence-based decision-making in academic planning and policy design

# Perspectives

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- Incorporate bootstrap resampling $\rightarrow$ variability of simulation parameters $\rightarrow$ robustness (under data scarcity)

# Agenda

# That’s all folks

# Now starts the Q ’n’ A session

**Praise the name of God forever and ever, for he has all wisdom and power. He controls the course of world events; he removes kings and sets up other kings. He gives wisdom to the wise and knowledge to the scholars. He reveals deep and mysterious things... (Daniel 2:20-22)**

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