Identifying Factors that Increase the Risk of Demotivation in Scientific Computing Courses Using Monte Carlo Methods

Isaac Caicedo-Castro*†‡ Rubby Castro-Púche†§ Oswaldo Vélez-Langs*‡
*Socrates Research Team
†Research Team: Development, Education, and Healthcare
‡Faculty of Engineering
§Faculty of Education and Human Science
University of Córdoba
Carrera 6 No. 76-305, 230002, Montería, Colombia
e-mail: {isacaic | rubycastro | oswaldovelez}@correo.unicordoba.edu.co

Abstract—**This study aims to identify the factors associated with the risk of demotivation in scientific computing courses. To achieve this, we modeled the functional relationship between student motivation and influencing factors using supervised machine learning, particularly Bayesian regression. This relationship was then incorporated into a Monte Carlo simulation to generate a wide range of scenarios, allowing us to estimate both absolute and relative risks of demotivation for each factor. In conclusion, the results reveal that the strongest predictors of increased demotivation risk are low levels of student satisfaction and enjoyment, followed by insufficient encouragement of independent study and limited access to up-to-date equipment, among other factors.**

Keywords-higher education; motivation; Bayesian regression; Monte Carlo methods.

I. Introduction

In this study, we identify the factors associated with an increased risk of demotivation among students enrolled in scientific courses. To this end, we applied regression and Monte Carlo statistical methods to estimate students' motivation levels across a wide input space defined by multiple motivation factors. These estimated motivation levels were then used to compute both the absolute and relative risks of demotivation.

Identifying these factors is essential for designing effective policies and implementing strategies to prevent or mitigate the risk of demotivation. Scientific courses, such as numerical methods, are particularly challenging because they combine mathematics, computer programming, and scientific domains (e.g., physics, chemistry, biology), each of which is already difficult on its own. Additional difficulties arise from the abstract mathematical concepts underlying scientific computing, as well as from students' struggles to understand how these methods can be applied to solve real-world problems across diverse scientific fields.

Reducing the risk of demotivation is critical, as demotivated students often lack the willingness or drive to complete assignments, prepare for examinations, and engage with learning activities. In the context of scientific computing courses, sustaining student motivation is particularly challenging.

For this study, we collected data from a community sample of students enrolled in the Systems Engineering bachelor's program at the University of Córdoba, Colombia. This dataset was used to estimate a function that predicts students' motivation based on the values of influencing factors

Using this functional dependency, we applied the Monte Carlo method to simulate a broader range of values for the influencing factors than those available in the dataset. The goal of this simulation was to estimate the risk of demotivation. In this context, simulation provides an appropriate alternative to avoid unethical experiments in which students would be exposed to stressful or unfavorable scenarios in order to directly observe demotivation risk.

The results of the Monte Carlo simulation indicate that targeted interventions are needed to design courses that foster student satisfaction and enjoyment, as both factors are strongly associated with a high risk of demotivation in scientific computing courses. Interventions are also necessary in prerequisite mathematics courses, since the greatest risk of demotivation was linked to students' experiences in prior mathematics coursework. Enhancing satisfaction and enjoyment in these foundational courses may therefore reduce the overall risk of demotivation in subsequent scientific computing studies.

Additional factors associated with the risk of demotivation include:

i) Access to up-to-date equipment to support scientific computing courses.
ii) Encouragement for independent study, cooperation, and collaborative coursework.
iii) Student focus and engagement in course activities.
iv) Student beliefs regarding the usefulness of the course and mathematics in general for their future professional life, their self-perceived ability to learn mathematics and solve mathematics-related problems, and their perception of the importance of hard work for successfully completing the course.

By adopting a Bayesian regression model, our study achieved a modest improvement in predictive performance, increasing the coefficient of determination from 0.37 reported in prior research [1] to 0.38. Moreover, unlike aforementioned previous research, we explicitly computed and analyzed both the relative and absolute risks associated with each factor linked to demotivation, thereby providing a more nuanced and actionable assessment of how these factors contribute to students' motivational outcomes.

Absolute risk represents the simulated probability of demotivation and reflects the practical impact of each factor on the student population. In contrast, relative risk measures the strength of association by comparing the probability of demotivation between exposed and non-exposed groups, thereby indicating the extent to which a given factor increases or decreases risk relative to a baseline condition. Taken together, these metrics enable the identification of factors that are not only statistically associated with demotivation but also substantively meaningful in practical terms.

The remainder of this paper is outlined as follows: we discuss the literature review in Section II, and present the methodology adopted in this research in Section III. We report and analyze the results in Sections IV and V. Finally, we conclude the paper in Section VI and propose directions for further research.

II. Prior Research

Learning scientific computing is challenging because students must integrate knowledge of mathematics, computer programming, and the sciences (e.g., physics, chemistry). Mathematics is essential for understanding how numerical methods work, while computer programming is required to implement them. Moreover, solving real-world engineering problems demands a solid grounding in science to understand the problem context and to apply numerical methods effectively.

This challenge has motivated research aimed at predicting which students are at risk of failing scientific computing courses based on their performance in prerequisite subjects [2][3]. Recent studies have even explored quantum machine learning approaches to address this problem [4]. Furthermore, prediction accuracy has been improved by adopting alternative representations of the independent variables, considering only student performance in prerequisite mathematics courses (i.e., linear algebra, differential, integral, and vector calculus) [5].

The findings in [5] highlight the importance of students' mathematics background for success in scientific computing courses. However, learning mathematics is itself a challenging task. Consequently, identifying the factors that influence mathematics learning has been a subject of extensive research, ranging from basic education [6][7][8][9] to higher education [10][11][12][13][14], and even at the doctoral level [15]. Scientific computing, essentially an applied mathematics discipline, encompasses numerical methods and heuristics for solving mathematical problems in science and engineering that cannot be addressed analytically.

In Colombia, studies have explored the process of knowledge construction among college students in the context of algebra courses within engineering curricula [11]. Previous research has primarily focused on students' commitment, satisfaction, and the challenges they face in learning mathematics at the college level.

Students' motivation for learning scientific computing has been investigated using machine learning, particularly regression, and the Monte Carlo method to estimate the probability that a student reaches one of ten motivation levels. The study was conducted with 117 students enrolled in scientific computing courses within the undergraduate Systems Engineering program at the University of Córdoba in Colombia. The results revealed that students are most likely to achieve moderate motivation levels, although effective policies and strategies could increase the probability of attaining higher levels of motivation [1].

In this paper, we estimate the functional dependency between independent and dependent variables using linear regression fitted with the No-U-Turn Sampler (NUTS) [16], a Hamiltonian Monte Carlo method. This differs from the previous study [1], which adopted Ridge Regression (cf. [17] for details). We then use the regression function to explore a broader space of independent variables in order to calculate the probability that a student reaches a specific motivation level, as in [1]. In addition, we estimate the absolute and relative risk of demotivation associated with the independent variables, an analysis that, to our knowledge, has not been conducted in prior research.

III. Research Methodology

We adopted a quantitative approach in which the factors assumed influence the students' motivation to study scientific computing courses are treated as independent variables, while the student's motivation level serves as the dependent variable (aka, target variable). Our goal is to estimate the functional dependency between the independent and dependent variables, i.e., to identify the function $g : \mathcal{X} \to \mathcal{Y}$ that maps, for the ith student, the independent variables represented by the D-dimensional vector $x_i \in \mathcal{X} \subset \mathbb{R}^D$ to the dependent variable $y_i \in \mathcal{Y} \subset \mathbb{R}$. Herein, we consider $D = 15$ independent variables.

Thus, the function $g(x_i)$ predicts motivation level of the ith student given their influential factors x_i. Henceforth, the vector x_i shall be referred to as the input variables or input vector, since its component serve as input to the function g. We consider the same input variables utilized in [1], as listed in Table I. Some of these variables are also used in [13][14]. Each factor is quantified on a scale from 1 to 5 and then rescaled to the interval $[0, 1]$. For instance, if the ith student perceives that the university provides up-to-date equipment and assigns this factor a value of 5, the corresponding input variable becomes $x_{i,5} = 1$.

On the other hand, the dependent variable is measured on a discrete scale from 1 to 10, where higher values indicate greater student motivation. Hereafter, y_i is referred to as the output variable, since the function g approximates it (i.e., $g(x_i) \approx y_i$).

We used the same dataset collected in 2024 by Caicedo-Castro et al. [1], which contains 117 examples obtained from a survey of students enrolled in scientific computing courses, specifically Numerical Methods and Nonlinear Programming. The identities of the students were anonymized. The input variables were selected using an F-test: if the null hypothesis of no linear relationship between a given input variable and the output variable was rejected (i.e., p-value $< 5 \times 10^{-2}$), the variable will be included for fitting the regression model.

Following this criterion, a total of 15 input variables were retained, as listed in Table I.

The histogram, shown in Figure 1, illustrates that the maximum motivation level was chosen by most of the students, namely, 48 out of 117 students (see Table II).

Given the dataset described above, we perform a Bayesian linear regression to estimate the function g that models the relationship between the predictors and student motivation. In this framework, the regression parameters are treated as random variables with prior probability distributions. The model is defined as:

$$\hat{y}_i = \beta^T x_i + \beta_0 + \epsilon_i \tag{1}$$

where the real-valued D-dimensional vector $\beta \in \mathbb{R}^D$ and the real number β_0 are the parameters or weights (aka., coefficients) of the function g. Besides, $\hat{y}_i$ denotes the predicted motivation level for student ith $\hat{y}_i \approx y_i$, $\epsilon_i \sim \mathcal{N}(0, \sigma)$ represents the error term, and σ is the standard deviation of the residuals. The prior distribution are specified as follows: $\sigma \sim \mathcal{N}(0, 1)$, and the weights $\beta_j \sim \mathcal{N}(0, 1)$, for $j = 0, \ldots, D$. Consequently, the likelihood of the observations is given by:

$$y_i \sim \mathcal{N}(\beta^T x_i + \beta_0, \sigma) \tag{2}$$

The regression model was implemented in PyMC[18], which performs Bayesian posterior sampling using the No-U-Turn Sampler (NUTS). NUTS is an extension of Hamiltonian Monte Carlo (HMC) that adaptively determines the number of leapfrog steps L, thereby avoiding the need to specify this tuning parameter manually. This is advantageous because choosing L too small induces random-walk behavior, whereas an excessively large L results in unnecessary computational overhead (cf. [16] for details). The sampler was run with 14 parallel chains, each drawing 3500 samples, and a target acceptance rate of 0.99 to reduce the likelihood of divergent transitions.

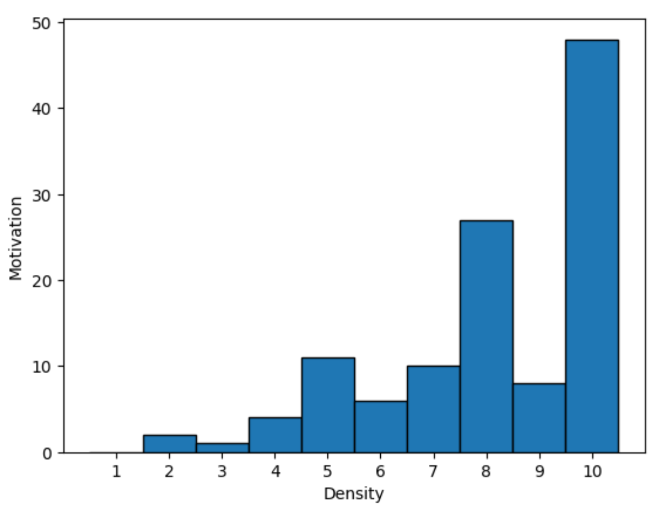

Figure 1. This histogram depicts the frequency with the students chose every level of motivation during the survey

Once the functional dependency between input and output variables was established, the function g was used to calculate the probability that students reach each motivation level. To accomplish this, we adopted the Monte Carlo method to simulate a broader input space than that available in the dataset [19]. This approach allows us to explore combinations of influencing factors not observed in the collected data, thereby providing a more comprehensive estimate of the risk of demotivation.

The probability that students achieve motivation level k for learning scientific computing is defined as follows:

$$P(y_i = k) \approx P(g(x_i) = k) = \int_{\mathcal{X}} P(g(x_i) = k \mid x_i) P(x_i)\, dx_i, \tag{3}$$

where $P(x_i)$ is the probability density function of the input variables.

Assuming that each component of x_i is uniformly distributed, i.e., $x_{ij} \sim \mathcal{U}(0, 1)$ for $j = 1, \ldots, D$, the probability density function $P(x_i)$ is uniform. Therefore, Equation (3) is rewritten as:

$$P(y_i = k) \approx P(g(x_i) = k) \approx \frac{1}{N} \sum_{i=1}^{N} \mathbf{1}(g(x_i) = k), \tag{4}$$

where N is the number of vectors x_i, whose components are random numbers uniformly distributed. Moreover, $\mathbf{1}(u) = 1$ if u is true, and $\mathbf{1}(u) = 0$ otherwise.

The value of N is chosen based on the standard error (SE), which is calculated as:

$$SE = \frac{\sigma}{\sqrt{N}}, \tag{5}$$

where σ is the standard deviation of the calculated probabilities. The value of N is increased iteratively until the SE decreases to a tolerable threshold.

The *Absolute Risk (AR)* of demotivation given the factor jth is not guaranteed is defined as follows:

$$AR(y_i < 5 \mid x_{ij} < 0.5) = \int_{\mathcal{X}} \frac{P(y_i < 5, x_{ij} < 0.5)}{P(x_{ij} < 0.5)}\, dx \tag{6}$$

Similarly, the AR of demotivation given the factor jth is guaranteed is defined as follows:

$$AR(y_i < 5 \mid x_j \geq 0.5) = \int_{\mathcal{X}} \frac{P(y_i < 5, x_{ij} \geq 0.5)}{P(x_{ij} \geq 0.5)}\, dx \tag{7}$$

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

$$RR(y_i < 5 \mid x_{ij} < 0.5) = \frac{AR(y_i < 5 \mid x_{ij} < 0.5)}{AR(y < 5 \mid x_j \geq 0.5)} \tag{8}$$

Using the Monte Carlo method the $AR(y_i < 5 \mid x_{ij} < 0.5)$ is calculated as follows:

TABLE I. INPUT VARIABLES ASSOCIATED TO THE FACTORS THAT INFLUENCE THE STUDENT'S MOTIVATION IN SCIENTIFIC COMPUTING COURSES

Input Variable	*F-statistic*	*p-value*
The student's average grade in previous mathematics courses	0.43	5.16×10^{-1}
The extent to which the student has felt good about the course† $x_{i,1}$	26.17	1.27×10^{-6}
The extent to which the student has felt good about previous mathematics courses† $x_{i,2}$	24.68	2.38×10^{-6}
The extent to which the student has enjoyed the course† $x_{i,3}$	37.08	1.54×10^{-8}
The extent to which the student considers it imperative to study the course	1.08	3.02×10^{-1}
The extent to which the student considers it imperative to study mathematics courses	0.99	3.22×10^{-1}
The extent to which the student considers it wrong not to study the course	0.40	5.26×10^{-1}
The extent to which the student considers it wrong not to study mathematics courses	1.30	2.56×10^{-1}
The extent to which the student would like to recommend the course to other peers† $x_{i,4}$	37.27	1.43×10^{-8}
The extent to which the student perceives that the university provides them with up-to-date equipment† $x_{i,5}$	8.43	4.42×10^{-3}
The extent to which the course has encouraged students to study with classmates† $x_{i,6}$	29.49	3.17×10^{-7}
The extent to which the student has been encouraged to help classmates† $x_{i,7}$	29.09	3.74×10^{-7}
The extent of the student's current engagement in participating in course lessons† $x_{i,8}$	20.43	1.51×10^{-5}
The extent of the student's current engagement in attending course lessons	2.04	1.56×10^{-1}
The extent of the student's current engagement in making an additional effort to understand the course† $x_{i,9}$	27.31	7.82×10^{-7}
The extent of the student's current focus and engagement during course lessons† $x_{i,10}$	27.59	6.96×10^{-7}
The extent to which the student has been encouraged to study the course independently† $x_{i,11}$	31.37	1.48×10^{-7}
The extent to which the student has believed the course is useful for their professional life† $x_{i,12}$	20.64	1.37×10^{-5}
The extent to which the student has considered mathematics courses useful for their professional life† $x_{i,13}$	12.94	4.75×10^{-4}
The extent to which the student has believed that they possess the ability to learn mathematics† $x_{i,14}$	3.30	7.17×10^{-2}
The extent to which the student has believed that they have the ability to solve mathematics-related problems	0.93	3.37×10^{-1}
The extent to which the student has enjoyed to solve challenging mathematics-related problems similar to those addressed in the course	15.02	1.77×10^{-4}
The extent to which the student feels their secondary school preparation is insufficient for succeeding in mathematics courses	3.67	5.79×10^{-2}
The extent to which the student believes people have innate abilities for mathematics	1.96	1.64×10^{-1}
The extent to which the student believes learning success depends on the lecturer	3.80	5.36×10^{-2}
The extent to which the student believes learning success depends on the student	1.62	2.06×10^{-1}
The extent to which the student believes hard work is key to succeeding in the course† $x_{i,15}$	4.29	4.07×10^{-2}

†The input variable is selected for regression

TABLE II. MOTIVATION LEVELS OF THE STUDENTS WHO ANSWERED THE SURVEY

Motivation Level	*Number of Students*	*Proportion of the Sample*
2	2	1.71%
3	1	0.85%
4	4	3.42%
5	11	9.40%
6	6	5.13%
7	10	8.55%
8	27	23.08%
9	8	6.84%
10	48	41.02%
Total	117	100.00%

$$AR(y_i < 5 \mid x_{ij} < 0.5) \approx \frac{\sum_{i=1}^{N} \mathbf{1}(y_i < 5 \wedge x_{ij} < 0.5)}{\sum_{i=1}^{N} \mathbf{1}(x_{ij} < 0.5)} \quad (9)$$

Similarly, the $AR(y_i < 5 \mid x_{ij} \geq 0.5)$ is calculated as follows:

$$AR(y_i < 5 \mid x_{ij} \geq 0.5) \approx \frac{\sum_{i=1}^{N} \mathbf{1}(y_i < 5 \wedge x_{ij} \geq 0.5)}{\sum_{i=1}^{N} \mathbf{1}(x_{ij} \geq 0.5)} \quad (10)$$

Furthermore, the relative risk is calculated as follows:

$$RR(y_i < 5 \mid x_{ij} < 0.5) \approx \frac{\frac{\sum_{i=1}^{N} \mathbf{1}(y_i<5 \wedge x_{ij} \geq 0.5)}{\sum_{i=1}^{N} \mathbf{1}(x_{ij} \geq 0.5)}}{\frac{\sum_{i=1}^{N} \mathbf{1}(y_i<5 \wedge x_{ij} \geq 0.5)}{\sum_{i=1}^{N} \mathbf{1}(x_{ij} \geq 0.5)}} \quad (11)$$

Finally, if a factor exerts a negative influence on motivation (i.e., its associated weight is negative), the interpretation of "high" versus "low" values of that factor is reversed. To account for this, we compute the relative risk as $RR(y_i < 5 \mid x_{ij} \geq 0.5)$ rather than $RR(y_i < 5 \mid x_{ij} < 0.5)$. This adjustment ensures that the calculation consistently reflects the condition under which the factor increases the probability of demotivation.

IV. RESULTS

We estimated the weights of the function $g(x_i) = \beta^T x_i + \beta_0$ adopting the above-mentioned Bayesian regression model. The estimated values of the weights are reported in Table III. The largest weights correspond to students' satisfaction ($x_{i,4}$) and enjoyment ($x_{i,3}$) with the scientific computing course.

The negative weight for $x_{i,13}$ suggests that students who perceive mathematics courses as useful tend to be slightly less motivated in scientific computing courses. One possible explanation is that these students are primarily motivated by achieving high grades while considering mathematical knowledge mainly as a graduation requirement. Alternatively, they might feel demotivated because they prefer solving problems through analytical approaches (more common in classical mathematics courses) in lieu of numerical methods, or heuristic, which are more common in scientific computing.

TABLE III. WEIGHTS OF THE PREDICTION FUNCTION ESTIMATED THROUGH THE BAYESIAN REGRESSION MODEL

Expected Weight	*97% CI*
$E[\beta_0] = 0.19$	[-1.224, 1.627]
$E[\beta_1] = 0.82$	[-0.718, 2.36]
$E[\beta_2] = 1.01$	[-0.38, 2.39]
$E[\beta_3] = 1.12$	[-0.44, 2.64]
$E[\beta_4] = 1.15$	[-0.45, 2.73]%
$E[\beta_5] = 0.45$	[-0.65, 1.55]
$E[\beta_6] = 0.52$	[-0.94, 1.94]
$E[\beta_7] = 0.89$	[-0.51, 2.33]
$E[\beta_8] = 0.56$	[-0.72, 1.84]
$E[\beta_9] = 0.83$	[-0.64, 2.31]
$E[\beta_{10}] = 0.79$	[-0.68, 2.25]
$E[\beta_{11}] = 1.01$	[-0.38, 2.38]
$E[\beta_{12}] = 0.35$	[-1.13, 1.817]
$E[\beta_{13}] = -0.38$	[-1.82, 1.08]
$E[\beta_{14}] = 0.27$	[-0.96 1.497]
$E[\beta_{15}] = 0.18$	[-1.148 1.499]

The Bayesian regression model adopted in this study achieved slightly better predictive performance than that reported by Caicedo-Castro et al. [1]. Our model attained a coefficient of determination (R^2) of 0.38 and a root-mean-squared error (RMSE) of 1.61, whereas the model in Caicedo-Castro et al. achieved an R^2 of 0.37 and an RMSE of 1.62. Although the improvement is marginal, it suggests that the Bayesian approach provides at least comparable, and potentially more robust, predictive accuracy.

Using the aforementioned function g, the results obtained from the Monte Carlo simulation revealed the most probable level is 4.98 with a standard error of 7×10^{-4}. Figure 2 illustrates how the simulation converges to this value as N increases. The estimate was obtained with 95% confidence (α = 0.05), yielding an interval [4.97, 4.98]. Since this value does not correspond to an actual motivation level, we rounded the result to the nearest even integer in halfway cases to ensure consistency with the discrete nature of the motivation scale (levels 1–10). The resulting probabilities of motivation levels are presented in Table IV.

TABLE IV. PROBABILITY OF EVERY MOTIVATION LEVEL CALCULATED WITH THE MONTE CARLO METHOD

Level	*Probability*
1	P(y = 1.0) = 1.22×10^{-4}%
2	P(y = 2.0) = 0.13%
3	P(y = 3.0) = 3.86%
4	P(y = 4.0) = 24.72%
5	P(y = 5.0) = 44.09%
6	P(y = 6.0) = 23.64%
7	P(y = 7.0) =3.46%
8	P(y = 8.0) = 9.78×10^{-2}%
9	P(y = 9.0) = 1.22×10^{-4}%

It is noteworthy that both the highest and lowest motivation levels have the smallest probabilities when the input variables are uniformly distributed across a broader space, as shown in Figure 3 and reported in Table IV. This suggests that extreme levels of motivation are less likely to occur under general conditions, and may instead arise from particular combinations of factors that are not equally represented in a uniform distribution. By contrast, the dataset indicates that students are predominantly highly motivated (see Table II in Section III), likely reflecting characteristics specific to the surveyed population rather than the broader input space.

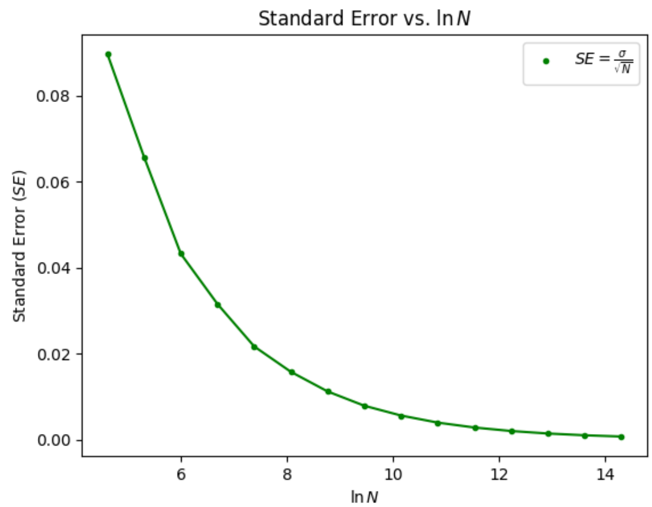

Figure 2. This chart shows how the standard error drops as the variable N is increased in the Monte Carlo simulation applied on the two-dimensional input space.

Satisfaction and enjoyment emerge as critical factors influencing the risk of demotivation, according to our simulation results. When the input space is explored through Monte Carlo methods, students who are unsatisfied with the scientific computing course and would not recommend it (i.e., input variable $x_{i,4}$) are more than twice as likely to become demotivated compared to satisfied students, with a relative risk of 2.41. In probabilistic terms, the simulation indicates that dissatisfaction raises the absolute risk of demotivation to 40.55%, while satisfaction reduces it to 16.85%. This corresponds to a risk difference of 23.7%, with a 95% confidence interval of [23.571, 23.838]. It is important to note that these figures do not reflect individual survey responses but instead arise from simulated projections across a broader range of possible student profiles. The results highlight how dissatisfaction can sharply elevate the probability of demotivation, underscoring the need to design course experiences that foster engagement and positive perceptions.

Moreover, the simulation results reveal that satisfaction and enjoyment, while related, are distinct factors influencing demotivation. Specifically, students who do not enjoy the scientific computing course (i.e., input variable $x_{i,3}$) are more than twice as likely to become demotivated compared to those who might be enjoying it, with a relative risk of 2.31. In absolute terms, lack of enjoyment increases the simulated risk of demotivation to 40.10%, while enjoyment reduces it to 17.31%. This yields a risk difference of 22.79%, with a 95% confidence interval of [22.653, 22.921]. Together with the results for satisfaction, these findings underscore that both enjoyment and satisfaction independently contribute to mitigating demotivation, and that guaranteeing an enjoyable learning experience is as crucial as ensuring a satisfactory one.

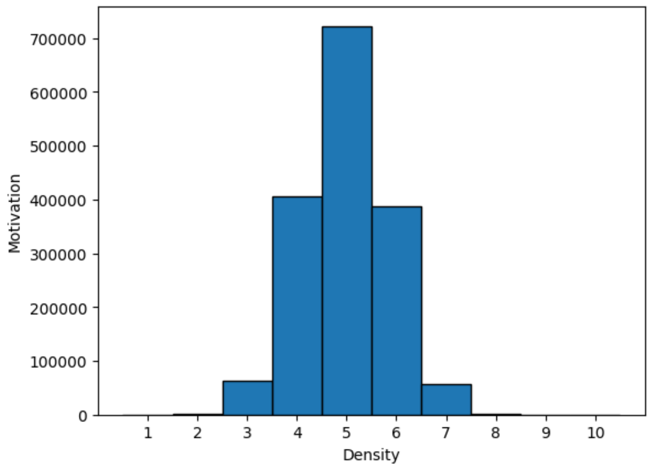

Figure 3. Histogram yielded through the Monte Carlo method. This shows the frequency with which the function g calculates each motivation level based on the random input variables.

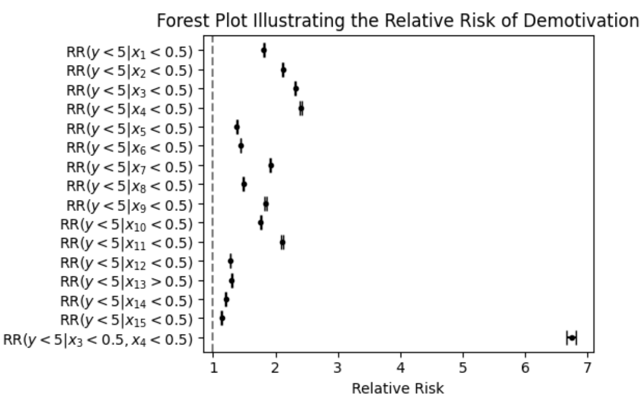

Figure 4. Forest plot showing the relative risk (RR) of failing the Physics II course. In all cases, the Wald test p-value is less than 0.05.

When both satisfaction and enjoyment are absent, the simulation shows a synergistic effect on the risk of demotivation. In this scenario, the absolute risk rises sharply to 54.54%, compared to only 8.09% among students who are both satisfied and enjoy the course. This corresponds to a risk difference of 46.45%, with a 95% confidence interval of [46.272, 46.619]. Put differently, the simulation indicates that students lacking both satisfaction and enjoyment are more than eight times as likely to become demotivated as their peers who experience both.

This combined effect is considerably stronger than the impact of each factor in isolation: dissatisfaction alone increases the absolute risk to 40.55%, while lack of enjoyment increases it to 40.10%. Thus, the simulation suggests that dissatisfaction and lack of enjoyment do not merely add up their effects, but instead interact to amplify the overall risk, underscoring the importance of addressing both factors simultaneously in the design of scientific computing courses.

Finally, the absolute and relative risks associated with the remaining factors are summarized in the forest plot shown in Figure 4 and detailed in Table V. This visualization provides a comparative view of how each factor contributes to the simulated risk of demotivation, allowing the relative importance of different influences to be assessed at a glance.

V. Discussion

The Monte Carlo method enables the estimation of demotivation risk in scientific computing courses without relying on direct experimentation with students, an approach that would be both unethical and impractical. This simulation-based framework therefore provides a valuable alternative for examining how different factors influence student motivation and for evaluating the prospective impact of educational policies. Whereas previous studies have primarily focused on predicting academic performance or identifying challenges associated with mathematical prerequisites, the present work extends this line of research by explicitly quantifying the risk of demotivation.

Fostering satisfaction, interest, and enjoyment in scientific computing requires designing courses in which students feel capable, perceive a clear sense of purpose, and experience continuous progress. Student satisfaction is enhanced when learning expectations are well defined and academic success is attainable; in this regard, transparent rubrics can help build confidence while reducing uncertainty and anxiety. In parallel, enjoyment increases when the learning experience is active, engaging, and meaningful, reinforcing students' intrinsic motivation and sustained involvement with course material.

Building on this contribution, the simulation results indicate that lecturers should prioritize fostering both satisfaction and enjoyment in scientific computing courses, as these factors consistently emerged as the strongest predictors of reduced demotivation. In other words, cultivating positive learning experiences may be as important as addressing cognitive challenges when designing effective courses.

Beyond satisfaction and enjoyment, the simulation results also indicate that encouraging independent study is a key factor in reducing the risk of demotivation. This finding suggests that lecturers should design learning environments that promote self-regulation, for example, by providing structured learning guides, formative assessments, and opportunities for collaborative problem-solving that still require individual accountability. At the same time, targeted interventions in prerequisite mathematics courses are needed to improve students' learning experiences. Redesigning these courses to emphasize conceptual understanding, applied problem-solving, and clear connections to scientific computing may help mitigate the negative impact of unfavorable prior experiences on student motivation.

From a pedagogical perspective, these findings underscore the importance of fostering self-regulated learning and im-

TABLE V. ABSOLUTE AND RELATIVE RISK OF DEMOTIVATION FOR LEARNING SCIENTIFIC COMPUTING.

Factor	**Absolute Risk (%) exposed**	**Absolute Risk (%) unexposed**	**Risk Difference (%)**	**Relative Risk (%)**	**95% CI (Relative Risk)**	**95% CI (Risk Differences)**
The student has not felt good about the course ($x_{i,1}$)	37	20.41	16.59	1.81	[1.803, 1.822]	[16.449, 16.721]
The student has not felt good about previous mathematics courses $x_{i,2<0.5}$	39	18.43	20.57	2.12	[2.105, 2.127]	[20.438, 20.708]
The student has not enjoyed the course ($x_{i,3}$)	40.10	17.31	22.79	2.32	[2.304, 2.329]	[22.653, 22.921]
The student would not recommend the course to other peers ($x_{i,4}$)	40.55	16.85	23.7	2.41	[2.384, 2.420]	[23.571, 23.838]
The student perceives the university lacks up-to-date equipment ($x_{i,5}$)	33.29	24.13	9.16	1.38	[1.373, 1.386]	[9.023, 9.298]
The course has not encouraged students to study with classmates ($x_{i,6}$)	33.9	23.53	10.37	1.44	[1.434, 1.448]	[10.237, 10.512]
The student has not been encouraged to help classmates ($x_{i,7}$)	37.78	19.65	18.13	1.92	[1.912, 1.932]	[17.990, 18.261]
The student lacks engagement to participate in course lessons ($x_{i,8}$)	34.35	23.07	11.29	1.49	[1.482, 1.497]	[11.150, 11.425]
The student lacks engagement to make an additional effort to understand the course ($x_{i,9}$)	37.22	20.22	17	1.84	[1.831, 1.850]	[16.860, 17.132]
The student struggles focus and lacks engagement during course lessons ($x_{i,10}$)	36.62	20.78	15.83	1.76	[1.753, 1.771]	[15.698, 15.971]
The student has been discouraged to study the course independently ($x_{i,11}$)	38.97	18.48	20.49	2.11	[2.097, 2.120]	[20.351, 20.621]
The student has believed the course is not useful for their professional life ($x_{i,12}$)	32.18	25.23	6.95	1.28	[1.269, 1.281]	[6.807, 7.083]
The student has considered mathematics courses useless for their professional life ($x_{i,13}$)	32.41	25.01	7.4	1.3	[1.290, 1.302]	[7.266, 7.542]
The student has believed that they lack the ability to learn mathematics ($x_{i,14}$)	31.35	26.07	5.28	1.2	[1.197, 1.209]	[5.146, 5.423]
The student believes hard work is not key to succeeding in the course ($x_{i,15}$)	30.55	26.87	3.68	1.14	[1.131, 1.142]	[3.538, 3.815]
The student has not enjoyed the course and would not recommend it to other peers ($x_{i,3}$ and $x_{i,4}$)	54.54	8.09	46.45	6.74	[6.668, 6.812]	[46.272, 46.619]

proving the design of prerequisite mathematics instruction. The simulation results reveal that neglecting factors such as students' encouragement to study independently and their prior experiences in mathematics courses is associated with an increased risk of demotivation, highlighting the need for coordinated instructional strategies that address both foundational preparation and autonomous learning skills.

To promote independent study, instructional approaches such as flipped classrooms, problem-based learning, and scaffolded assignments can be particularly effective, as they combine learner autonomy with structured pedagogical support. These methods encourage students to take responsibility for their learning while ensuring they receive ongoing guidance and formative feedback.

Flipped classrooms, or flipped learning, reverse the traditional instructional model in which lecturers deliver content during class time and students complete practice activities at home. In this approach, students engage with instructional materials (such as, e.g., readings, videos, or interactive resources) prior to class, allowing face-to-face time to be devoted to problem-solving, discussion, project work, and direct interaction with the lecturer. As a result, students assume a more active role in the learning process, which promotes deeper engagement by transforming class sessions into interactive rather than passive experiences. Moreover, flipped learning supports self-paced study, enabling students to revisit materials as needed and thereby gain greater control over their learning process.

Flipped learning can be effectively combined with problem-based learning, where class time is dedicated to addressing real, open-ended problems rather than listening to traditional lectures. In this integrated approach, students are motivated to acquire the concepts, theoretical knowledge, and practical skills necessary to solve the problems posed in class. At the same time, they strengthen their ability to engage in independent study and develop critical thinking skills through active inquiry and collaborative problem-solving.

Scaffolded assignments can be used to complement both flipped learning and problem-based learning. These assignments are designed to provide structured, temporary support that helps students gradually build the skills and competencies required to work independently. The educational concept of scaffolding is inspired by the construction scaffold, which supports workers during the building process and is progressively removed as the structure becomes self-sustaining.

In order to improve the design of prerequisite mathematics instruction for scientific computing, coursework should focus on preparing students to model, simulate, and reason algorithmically. Mathematics courses can be oriented around applied use cases relevant to scientific computing, such as linear algebra for analyzing the stability of numerical solvers, differential calculus for numerical optimization and differentiation, and integral calculus for Monte Carlo estimation. In this approach, mathematics is taught through algorithms rather than solely through symbolic manipulation, enabling students to implement methods, explore numerical error and conditioning, visualize results, and work with approximations, thereby strengthening the practical connections between mathematical theory and computational application.

Strengthening prerequisite mathematics courses requires conceptual teaching approaches that deliberately connect abstract ideas with practical applications in scientific computing. Instructional strategies such as contextualized problem-solving, interdisciplinary projects, and active learning techniques (e.g., peer instruction and inquiry-based exercises) can make mathematics more meaningful and directly relevant to students' future coursework. Together, these pedagogical approaches not only help reduce the risk of demotivation but also foster continuity between foundational mathematical training and applied scientific computing.

In contrast, students' beliefs show a relatively weak association with the risk of demotivation. Perceptions such as viewing hard work as unimportant for success in scientific computing, doubting one's ability to learn mathematics, or considering mathematics or scientific computing to have little practical value are associated with comparatively low relative risks. Moreover, the corresponding differences in absolute risk are substantially smaller than those observed for other factors, indicating a limited practical impact of these beliefs on demotivation.

The weak association observed between students' beliefs and demotivation suggests that these beliefs may function as mediating factors rather than direct determinants of motivational outcomes. Negative beliefs concerning effort, ability, or the value of mathematics and scientific computing may develop in response to prior learning experiences, including academic difficulty, ineffective instructional practices, or early failure. Consequently, experiential conditions may shape learning outcomes first, followed by adjustments in students' beliefs, with demotivation emerging thereafter. Because the regression model includes variables with stronger effects (such as, e.g., satisfaction and enjoyment) the independent contribution of beliefs is attenuated, resulting in comparatively low relative risks and small absolute risk differences associated with these factors.

Limited access to up-to-date equipment also exhibits a relatively low relative risk and a small absolute risk difference. In contemporary educational contexts, this factor is not a dominant barrier to student motivation, as the tasks typically performed in scientific computing courses do not require high-performance hardware. Consequently, inadequate equipment alone is unlikely to constitute a substantial contributor to demotivation.

When most students have adequate access to functional equipment, or when mitigation strategies are widely available through appropriate instructional design, the exposed group (those who truly lack usable hardware) becomes small and heterogeneous. This statistical compression reduces discriminative power and biases both relative and absolute risk estimates toward modest values. Furthermore, scientific computing courses frequently make use of platforms such as Google Colab, which allow students to access sufficient computational resources even from low-spec devices, including smartphones.

Finally, it is important to acknowledge the methodological scope of this study. Expanding the dataset to include additional explanatory variables and a larger number of observations, as well as adopting more sophisticated models capable of capturing nonlinear relationships between inputs and outcomes, could further improve predictive performance. These enhancements may reduce the root-mean-square error and increase the coefficient of determination, thereby strengthening the robustness and validity of the simulation results. Overall, by integrating computational simulation with pedagogical analysis, this work contributes methodologically to educational research while offering practical guidance for enhancing student motivation in scientific computing courses.

VI. Conclusion and Perspectives

We employed the Monte Carlo statistical method to estimate the absolute and relative risk of student demotivation in undergraduate scientific computing courses within the Systems Engineering program at the University of Córdoba (Colombia). This approach enabled the simulation of a large number of scenarios that cannot be examined empirically, thereby allowing exploration of a broad range of values for the independent variables representing factors associated with student motivation, the dependent variable of the study. The relationships between these factors and motivation were quantified using Bayesian regression, which provided the functional dependencies used as inputs for the simulation.

The results of the Monte Carlo simulations indicate that the factors most strongly associated with increased risk of demotivation are: i) students' satisfaction with the scientific computing course, ii) the level of enjoyment perceived by students during the course, iii) students' experiences in prerequisite mathematics courses, and iv) discouragement toward independent learning.

A hybrid pedagogical approach that integrates flipped instruction, scaffolded assignments, problem-based teamwork, and frequent formative feedback may offer an effective course design for enhancing student motivation while maximizing enjoyment and satisfaction in scientific computing. Such an approach aims to reduce anxiety, support the development of competence, increase the perceived relevance of learning activities, foster autonomy, and strengthen social connection, thereby improving the likelihood that students remain motivated and engaged throughout the course.

Additional simulation findings reveal that students' beliefs about effort, personal ability, and the relevance of mathematics and scientific computing are associated with a relatively low risk of demotivation. Similarly, the availability of up-to-date equipment at the university shows only a minor association with demotivation risk, suggesting that these factors exert a limited practical influence compared with the primary predictors identified in the study.

For future research, we shall conduct intervention testing and instructional design evaluations through controlled trials that compare pedagogical approaches such as scaffolded instruction, flipped learning, and problem-based learning. These studies will aim to verify whether and to what extent these strategies effectively enhance student motivation in scientific computing courses.

So far, we have assumed a linear relationship between student motivation and its influencing factors. In future work, we plan to explore nonlinear regression models in which the independent variables are mapped into higher-dimensional feature spaces. Such approaches may better capture complex interactions among factors, potentially increasing the coefficient of determination while reducing the root-mean-squared error.

Additionally, we shall apply dimensionality reduction techniques (such as, e.g., principal component analysis, matrix factorization, and autoencoders) to identify latent factors underlying student motivation. These methods may provide more compact and informative representations of the independent variables by filtering noise and capturing the most relevant structure in the data, thereby improving the performance and interpretability of the regression models.

Another extension of this research is the development of Monte Carlo–based causal simulations to move beyond risk association toward explicit counterfactual policy evaluation. Under this approach, a probabilistic causal structure (derived from methods such as Bayesian causal networks, structural equation modeling, or quasi-experimental estimators) is specified and used as a generative model of the educational system. Large numbers of simulated student trajectories can then be sampled under alternative interventional scenarios (e.g., enhanced instructional quality or the introduction of scaffolded assignments) using the logic of do-calculus. This framework enables the estimation of causal quantities such as the expected reduction in demotivation, changes in satisfaction levels, and heterogeneity of intervention effects across student subgroups, all while accounting for uncertainty.

Monte Carlo causal simulation is particularly well suited to educational research because it can capture the nonlinear dynamics, mediation pathways, interaction effects, and threshold behaviors inherent to learning processes—phenomena that are difficult to isolate using closed-form regression models alone. This approach enables the evaluation of complex, multicomponent interventions rather than single-factor manipulations, for example by assessing whether moderate, coordinated improvements across several instructional dimensions yield larger motivational gains than major changes in only one area. In addition, sensitivity analyses can be directly integrated into the simulation framework to quantify how unmeasured confounding, measurement error, or parameter uncertainty propagate into causal predictions, thereby providing more transparent and realistic uncertainty bounds than conventional point estimates.

Finally, implementing this framework would enable a shift from descriptive modeling toward decision-support analytics for curricular and pedagogical design. Simulated policy experiments could identify which combinations of instructional interventions are most cost-effective, determine which student profiles benefit most from targeted support, and reveal points at which diminishing returns occur.

Acknowledgment

Caicedo-Castro thanks the Lord Jesus Christ for blessing this project. The authors thank Universidad de Córdoba in Colombia for supporting this study. They also thanks all students who collaborated by answering the survey conducted for collecting the dataset used in this study. Finally, the author thanks the anonymous reviewers for their comments that contributed to improve the quality of this article.

References

[1] I. Caicedo-Castro, O. Vélez-Langs, and R. Castro-Púche, “Using the Monte Carlo Method to Estimate Student Motivation in Scientific Computing”, in *PATTERNS 2025: The Seventeenth International Conferences on Pervasive Patterns and Applications*, ser. International Conferences on Pervasive Patterns and Applications, Valencia, Spain: IARIA: International Academy, Research, and Industry Association, 2025, pp. 15–22, ISBN: 978-1-68558-263-0.

[2] I. Caicedo-Castro, M. Macea-Anaya, and S. Rivera-Castaño, “Early Forecasting of At-Risk Students of Failing or Dropping Out of a Bachelor’s Course Given Their Academic History - The Case Study of Numerical Methods”, in *PATTERNS 2023: The Fifteenth International Conference on Pervasive Patterns and Applications*, ser. International Conferences on Pervasive Patterns and Applications, Nice, France: IARIA: International Academy, Research, and Industry Association, 2023, pp. 40–51, ISBN: 978-1-68558-049-0.

[3] I. Caicedo-Castro, “Course Prophet: A System for Predicting Course Failures with Machine Learning: A Numerical Methods Case Study”, *Sustainability*, vol. 15, no. 18, 2023, 13950. DOI: 10.3390/su151813950.

[4] I. Caicedo-Castro, “Quantum Course Prophet: Quantum Machine Learning for Predicting Course Failures: A Case Study on Numerical Methods”, in *Learning and Collaboration Technologies*, P. Zaphiris and A. Ioannou, Eds., Cham: Springer Nature Switzerland, 2024, pp. 220–240, ISBN: 978-3-031-61691-4. DOI: 10.1007/978-3-031-61691-4_15.

[5] I. Caicedo-Castro, “An Empirical Study of Machine Learning for Course Failure Prediction: A Case Study in Numerical Methods”, *International Journal on Advances in Intelligent Systems*, vol. 17, no. 1 and 2, pp. 25–37, 2024.

[6] L. Ayebale, G. Habaasa, and S. Tweheyo, “Factors Affecting Students’ Achievement in Mathematics in Secondary Schools in Developing countries: A Rapid Systematic Review”, *Statistical Journal of the IAOS*, vol. 36, pp. 1–4, 2020. DOI: 10.3233/SJI-200713.

[7] M. Gómez-García, H. Hossein-Mohand, J. M. Trujillo-Torres, H. Hossein-Mohand, and I. Aznar-Díaz, “Technological Factors That Influence the Mathematics Performance of Secondary School Students”, *Mathematics*, vol. 8, no. 11, 2020, 1935, ISSN: 2227-7390. DOI: 10.3390/math8111935.

[8] J.-M. Trujillo-Torres, H. Hossein-Mohand, M. Gómez-García, H. Hossein-Mohand, and F.-J. Hinojo-Lucena, “Estimating the Academic Performance of Secondary Education Mathematics Students: A Gain Lift Predictive Model”, *Mathematics*, vol. 8, no. 12, 2020, 2101, ISSN: 2227-7390. DOI: 10.3390/math8122101.

[9] M. Maamin, S. M. Maat, and Z. H. Iksan, “The Influence of Student Engagement on Mathematical Achievement among Secondary School Students”, *Mathematics*, vol. 10, no. 1, 2022, 41, ISSN: 2227-7390. DOI: 10.3390/math10010041.

[10] A. Brezavšček, J. Jerebic, G. Rus, and A. Žnidaršič, “Factors Influencing Mathematics Achievement of University Students of Social Sciences”, *Mathematics*, vol. 8, no. 12, 2020, 2134, ISSN: 2227-7390. DOI: 10.3390/math8122134.

[11] E. Martinez-Villarraga, I. Lopez-Cobo, D. Becerra-Alonso, and F. Fernández-Navarro, “Characterizing Mathematics Learning in Colombian Higher Distance Education”, *Mathematics*, vol. 9, no. 15, 2021, 1740, ISSN: 2227-7390. DOI: 10.3390/math9151740.

[12] J. Park, S. Kim, and B. Jang, “Analysis of Psychological Factors Influencing Mathematical Achievement and Machine Learning Classification”, *Mathematics*, vol. 11, no. 15, 2023, 3380, ISSN: 2227-7390. DOI: 10.3390/math11153380.

[13] S. Batista-Toledo and D. Gavilan, “Student Experience, Satisfaction and Commitment in Blended Learning: A Structural Equation Modelling Approach”, *Mathematics*, vol. 11, no. 3, 2023, 749, ISSN: 2227-7390. DOI: 10.3390/math11030749.

[14] M. Charalambides, R. Panaoura, E. Tsolaki, and S. Pericleous, “First Year Engineering Students’ Difficulties with Math Courses- What Is the Starting Point for Academic Teachers?”, *Education Sciences*, vol. 13, no. 8, 2023, 835, ISSN: 2227-7102. DOI: 10.3390/educsci13080835.

[15] T. T. Wijaya, B. Yu, F. Xu, Z. Yuan, and M. Mailizar, “Analysis of factors affecting academic performance of mathematics education doctoral students: A structural equation modeling approach”, *International Journal of Environmental Research and Public Health*, vol. 20, no. 5, 2023, 4518, ISSN: 1660-4601. DOI: 10.3390/ijerph20054518.

[16] M. D. Hoffman and A. Gelman, “The No-U-Turn Sampler: Adaptively Setting Path Lengths in Hamiltonian Monte Carlo”, *Journal of Machine Learning Research*, vol. 15, no. 47, pp. 1593–1623, 2014.

[17] C. M. Bishop, *Pattern Recognition and Machine Learning (Information Science and Statistics)*. Berlin, Heidelberg: Springer-Verlag, 2006, ISBN: 0387310738.

[18] O. Abril-Pla et al., “PyMC: a Modern, and Comprehensive Probabilistic Programming Framework in Python”, *PeerJ Computer Science*, vol. 9, no. 1516, 2023, ISSN: 2376-5992. DOI: 10.7717/peerj-cs.1516.

[19] N. Metropolis and S. Ulam, “The Monte Carlo Method”, *Journal of the American Statistical Association*, vol. 44, no. 247, pp. 335–341, 1949, ISSN: 01621459, 1537274X.