**Bulletin of Electrical Engineering and Informatics**
Vol. 13, No. 5, October 2024, pp. 3446~3454
ISSN: 2302-9285, DOI: 10.11591/eei.v13i5.7562 

# System dynamics modeling for predicting the impact of tutoring on student retention in the school of engineering

**Laberiano Andrade-Arenas[1], Margarita Giraldo Retuerto[1], Cesar Yactayo-Arias[2]**
[1]Facultad de Ciencias e Ingeniería, Universidad de Ciencias y Humanidades, Lima, Perú
[2]Departamento de Estudios Generales, Universidad Continental, Lima, Perú

**Article Info**

***Article history:***

Received Sep 16, 2023
Revised Mar 1, 2024
Accepted Mar 20, 2024

***Keywords:***

Modeling
Student desertion
System dynamics
Systemic approach
Vensim

**ABSTRACT**

Student retention is a persistent problem in many educational institutions, and we seek to address this issue through the implementation of tutoring programs. To achieve this objective, system dynamics (SD) modeling is proposed as a method. This analytical tool allows simulating and predicting the behavior of a complex system over time, considering the interactions between its components. The main objective of this research is to perform SD modeling to improve student retention through tutoring. It seeks to design more effective and personalized tutoring programs, adapted to the specific needs and challenges of the institution's students. The results obtained show that, in the period between 2022 and 2026, research degrees will be encouraged, reaching 50% participation. This increase is considered a positive indicator that encourages universities to become research protagonists. In conclusion, SD modeling makes it possible to forecast and strategically plan the expected results in terms of student retention. This method provides tools to more effectively address the problem of retention, ensuring the academic success of students and promoting the participation of universities in research.



***Corresponding Author:***

Cesar Yactayo-Arias
Departamento de Estudios Generales, Universidad Continental
Lima, Perú
Email: cyactayo@continental.edu.pe

## 1. INTRODUCTION

A highly competitive international context, student retention in educational institutions has become a critical challenge to ensure the success and quality of higher education [1]. Student retention is a key indicator of the effectiveness of an academic program and can have a significant impact on the reputation and performance of an institution [2]. In this regard, tutoring has emerged as a promising strategy to improve student retention worldwide [3].

Tutoring is an educational approach that seeks to provide individualized support to students, offering guidance and personalized assistance in academic areas [4], study skills and adaptation to university life [5]. These tutorials can be conducted by professors, specialized tutors or even more advanced students acting as mentors [6]. The benefits of tutoring go beyond academic support, as they also foster students' personal development, motivation and sense of belonging [7]. Despite efforts to improve student retention, attrition remains a persistent challenge in many higher education institutions worldwide. Lack of individualized support and insufficient adaptation to the university environment are factors that contribute to student dropout [8]. In this regard, tutoring has been recognized as an effective strategy to address these problems and improve student retention [9]. However, although it has been shown that tutoring can have a positive impact on student retention, its implementation and effectiveness may vary according to the context and characteristics of each institution. There is a need to better understand how tutoring influences student retention in the College of Engineering, specifically, and how more effective tutoring programs can be designed to address the particular needs and challenges of engineering students [10].

The importance of this research lies in its potential to inform decision making and strategic planning in the implementation of mentoring programs in the College of Engineering and potentially in other educational institutions internationally [11]. By better understanding how tutoring can influence student retention, more effective and personalized strategies that promote engineering student retention can be designed [12]. This research will directly benefit the College of Engineering, its faculty, tutors, and students by providing tools and knowledge that will enable them to improve student retention and academic success. In addition, the academic community and educational institutions in general will also benefit by having a greater understanding of the dynamics and factors that influence student retention through tutoring [13].

This study proposes to use system dynamics (SD) models to predict how tutoring will affect the likelihood that students will remain in the School of Engineering [14]. As part of this process, it is necessary to build a model that accounts for the interaction among the many components of the system, including the tutoring program, students, faculty, and other aspects [15]. This model can be used to simulate and analyze the impact of various tutoring tactics on student retention, allowing for predictions and evaluations. The present research aims to provide a deeper understanding of how SD modeling can be applied to forecast the impact of tutoring on the retention of engineering students. SD modeling is an analytical tool that allows simulating and predicting the behavior of a complex system over time, considering the interactions between its different components.

## 2. LITERATURE REVIEW

Aggarwal *et al.* [16], emphasize that academic institutions are placing increasing emphasis on employing various data mining approaches to improve student performance. To enable early adoption of preventive interventions, predictive models are created to forecast student performance at an incredibly early level. Using a variety of classifiers, various academic and non-academic characteristics are taken into account to predict student performance. Academic indicators often carry more weight in predicting a student's performance in class. In this essay we compare the two models, one created using only academic parameters and the other using both academic and non-academic parameters. The main student data collection, which included information on 6,807 individuals and attributes, was obtained from a technical university in India. To handle the biased data set, a synthetic minority oversampling approach filter is used. Eight classification algorithms are used to build the models, which are then compared to determine the features that will best help classify a student based on performance.

Research on measures of college student retention often focuses on the issue of dropout. However, few studies have examined when and how best to identify students at risk of dropping out. Ortiz-Lozano *et al.* [17], used demographic and academic information from 935 first-year students at a Spanish engineering school to perform a classification tree-based dropout prediction analysis. They also used data obtained at three points in time throughout the first semester of the first year to build predictive models. The results they obtained coincide with those of other research highlighting the importance of intervention in the first year to reduce dropout rates. Academic performance data are also a useful predictor.

On the other hand [18], they state that students from all academic fields, not only engineering, can learn and contribute to this exciting field of study. This paper presents research that will be incorporated into a didactic module on the subject, and was written by graduate students in electrical, industrial and mechanical engineering. Academics and specialists in the field collaborated in the development of this program. Various types of sensors are being investigated to track gait and determine a person's susceptibility to falls. The current status of balance-related sensor technologies is being studied. Models of human standing balance are being studied, and a simulation tool was created to allow them to experiment with different values of the model parameters. In this way, engineering students can test the relevance of their studies to solve a pressing social problem. This study details the structure to be used in an educational module that will introduce graduate students to multidisciplinary research topics, while reinforcing the understanding of engineering fundamentals at the undergraduate level through experiments and simulations of equilibrium dynamics.

Discrete event simulation (DES) and SD are two different types of simulation, and Tako and Robinson [19], in their research, perform an experimental analysis on an analysis of students to predict the impact of tutoring. However, they mention that not enough previous comparative work has been done, and much of what has been done is based on the subjective opinions of the authors. In this study, the opinions of engineering student managers were used to compare and contrast student retention with an identical simulation model and SD. The research concluded that, from the perspective of the end users of the model, there are no discernible differences between DES and SD in education. Differences in model complexity and validity were found to be rather small. The results were examined in a SD to understand and analyze the impact of tutoring on engineering students.

Student success can be measured in terms of exam results and course completion using this tool. It does this by analyzing a data set consisting solely of details on students, degrees and courses of study routinely collected by university administrations. The online resource makes available the results of numerous analyses. Also, Prada *et al.* [20], perform an analysis of student data in a low-dimensional representation using clustering and visualization helps to identify trends. Coordinated visualization of aggregated student performance in histograms, which are automatically updated based on custom filters applied interactively by an analyst, can help validate assumptions regarding a group of students. The extent to which students' behavior in a given grade depends on the courses in which they are enrolled can be better understood by classifying students who have already graduated into three performance levels using exploratory variables and early performance information. Similarly, Drago *et al.* [21], synthesize that the causes of dropout can be better understood by analyzing the effect of explanatory variables and early performance on the probability of graduation. The final implementation of the web tool for this project was defined by preliminary testing with engineering student data from the six partner institutions [22]. Initial classification and elimination results were satisfactory, with accuracies above 90% in some cases. They analyzed the potential of the tool to help develop preliminary student profiles and its usefulness in light of the objectives set.

Finally, Destin *et al.* [23], detail that adolescents, in particular, are susceptible to seeing their own attitudes and behaviors influenced by those of their peers. However, experimental studies have not shown that closer and more experienced peers can have a beneficial effect on key characteristics of student motivation that predict later academic performance. Eighth graders were randomly assigned to either a mentoring treatment group or a mentoring control group, both led by randomly selected and trained high school students, and the results were analyzed in a randomized, controlled field trial. Results showed that, compared to the control group, individuals in the treatment group were more likely to appraise academic obstacles and persist through them, which could have significant implications for academic performance and peer tutoring programs.

In reviewing the selected research articles, several findings and the importance of mentoring in college student retention were identified. Also, by evaluating the current state of research, new ideas were obtained to make the research innovative. For all these reasons, an exhaustive bibliographic study was carried out. This analysis will allow better decisions to be made and winning tactics to be created. The overall goal of this literature review is to foster the growth and success of mentoring in engineering students through the use of data-driven strategies.

## 3. METHOD

Understanding and addressing the complexity of dynamic systems requires an analytical and modeling technique known as SD method. It is based on the concept that systems are networks of parts that change and adapt over time through mutual interactions. Flow diagrams or causal diagrams are used in SD to graphically illustrate causal links and the exchange of data [24], energy or other substances between system nodes. These diagrams show how a single adjustment of a variable can have far-reaching effects on the rest of the system. In other words, the consequences of one action can influence the future behavior of the system. This helps us understand the nonlinear behaviors and dynamics of complex systems by showing how changes in one area of the system can have cumulative or delayed effects on other parts. Figure 1 shows the relationship of SD method to information, decision and action.

### 3.1. Causal diagram

A causal diagram is a graphical representation of the links between system variables that reveal their underlying causes. Each variable is represented by a box or node, and the connections between them are shown by arrows. These arrows represent the relationship between two variables when one of them is altered. By representing the interrelationships and dependencies between variables, the causal diagram helps to pinpoint the causes of system behavior [25]. It is also useful for finding feedback loops, which are cycles of influence between two or more factors. There are two types of feedback loops: positive feedback, in which the change in one variable promotes the change in another, and negative feedback, in which the change in one variable act to rectify or compensate for the change in another. The causal diagram is a useful tool for analyzing complex systems because it highlights possible sites of intervention and helps us to see how a change in one variable can have knock-on effects on others. Figure 2 shows a causal diagram modeling of the impact of tutoring on engineering student retention.

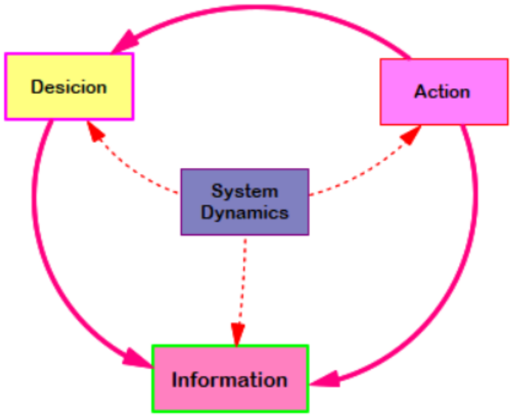


Figure 1. SD method

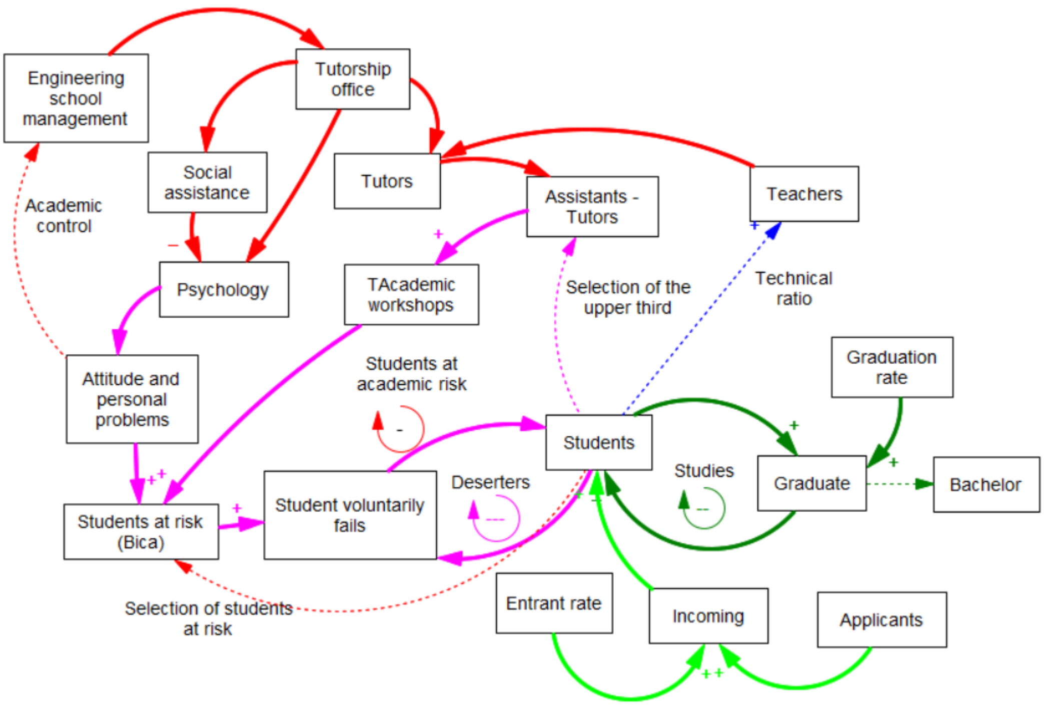


Figure 2. Causal diagram of Ramírez [26]

### 3.2. Forrester's diagram

Forrester diagrams sometimes referred to as stock-flow diagrams and flow diagrams, are used in SD to graphically illustrate the time-varying behavior of a system. Stocks are represented by boxes or nodes, while flows are represented by arrows entering or leaving the stock [27]. Stocks, inventories and financial assets are examples of stocks, while cash flows are examples of how stocks fluctuate over time. This type of chart allows us to model and understand the evolution of variables in response to flows and their associated causal links. The Forrester diagram to analyze data for good informed decision making on interventions or policies because it illustrates the accumulation or depletion of stocks over time and the non-linear interactions between factors in a system. Figure 3 shows a Forrester diagram modeling the impact relationship of tutoring on student retention.

### 3.3. Formulas

A system model is represented by formulas, which are mathematical tools used in SD. These formulas make it possible to determine the values of variables as a function of other variables and system characteristics. These equations make it possible to model and simulate various scenarios, to understand the dynamics of complex systems and to evaluate the results of possible interventions or policies. The formulas used in SD can be as simple as an addition or multiplication, or as complex as an equation that includes growth rates, feedbacks or interactions between variables. These equations provide a quantitative framework for understanding the temporal and interdependent nature of system variables, allowing more informed decisions to be made and more effective strategies to be developed to improve system performance and functionality. Table 1 shows the formulas for SD simulation to improve the quality of models on tutoring in student retention.

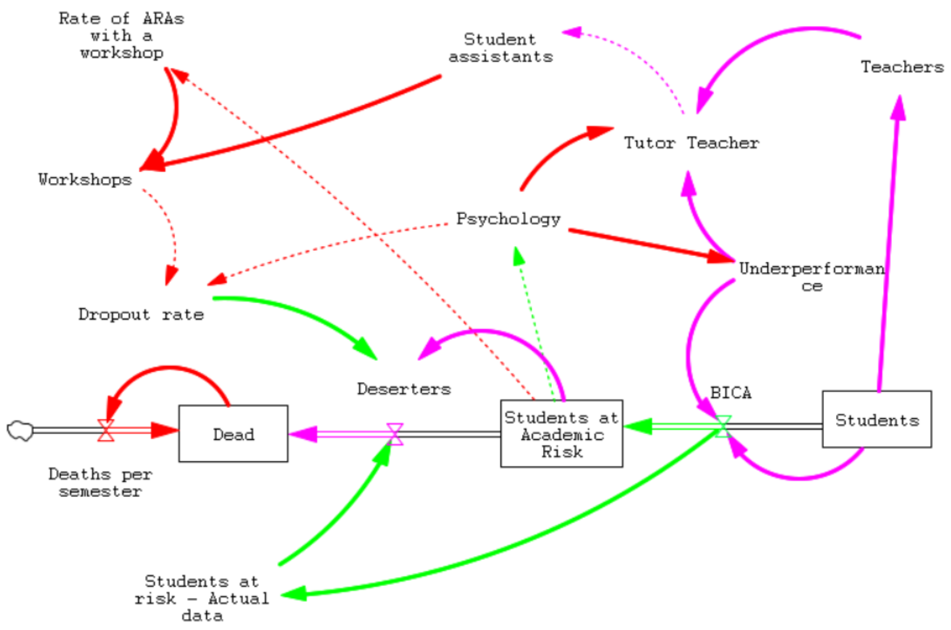


Figure 3. Forrester diagram of Ramírez [26]

Table 1. Simulation formulas

| Variables | Formulas |
|---|---|
| 1 | Alumni=students+qualified entrants-studies-Bica |
| 2 | At-risk students=Bica-dropouts |
| 3 | Baccalaureates=baccalaureates*0.30 |
| 4 | Ratio=max (graduation rate * graduates) |
| 5 | Student recruitment=capable+competency training |
| 6 | Semester revaluation=number of classrooms+semester |
| 7 | Loop=Attendance rate*workshop rate |
| 8 | Mentor teachers=teachers+psychology |
| 9 | Entrants=applicants*entrant rate |
| 10 | ARA rate=Student attendance/operational workshops |
| 11 | Psychology=underperformance+Competence training |
| 12 | Deaths per semester=Bica+dead |

### 3.4. Data

Research, modeling and validation of system models rely heavily on data in SD. Measurements are examples of the types of information that constitute data. Input data for simulations, model validation and fitting, and initial value estimation depend on these data. In addition, the data can be used to calibrate and evaluate model formulas and relationships, ensuring that they accurately represent the behavior of the real system. The data can be used to test model assumptions and hypotheses, ensuring that the model is as accurate and reliable as possible. In addition, the performance of the model and its ability to anticipate system behavior under various scenarios can be evaluated by comparing simulation results with actual data. In conclusion, the understanding and analysis of complex systems relies heavily on SD data, which is crucial to both support and improve the quality of models on tutorials in the retention of undergraduate engineering students Table 2.

Table 2. Data for the sample of results

| Num | Data |
|---|---|
| 1 | Workshop rate=1% |
| 2 | Variation=100 |
| 3 | Engineering student population=0.2 |
| 4 | ARA students=3.50% |
| 5 | Dropout rate=4.2% |
| 6 | Student recruitment=20 |
| 7 | Baccalaureate=20% |
| 8 | Production competence training=42% |
| 9 | Engineering degree=2% |
| 10 | Psychology=30% |
| 11 | Workshop rate=28% |

## 4. RESULTS AND DISCUSSION

The results of a SD model can be understood by analyzing simulated data and trends. The study of SD reveals the interaction and change of system variables over time. Therefore, the goal of SD analysis is to recognize emerging behaviors and trends in model variables. The results of the SD can be understood through the underlying causal diagram and Forrester diagram and the knock-on effects of these changes. The possible domino effects of these alterations and their temporal progression are investigated. The long-term effects on the impact of tutoring on the retention of engineering students are also investigated. Additionally, Ortiz-Lozano *et al.* [17] used information from 935 first-year students from an engineering school to perform a dropout prediction analysis by applying a classification tree, and predictive models were built. The results obtained focus on intervention in the first year to reduce school dropout rates, with data on academic performance being a predictor. The difference is that the first uses simulation at a certain time and the second makes predictions by applying data mining.

Students who have dropped out are represented in Figure 4 one curve (labeled "Dead") represents students who have had to abandon their studies, while the other (labeled "Graduates") represents those who have successfully completed their degrees. Fortunately, the number of "Graduates" has always exceeded the number of "Dies". However, because of this ratio, it was necessary to prepare a larger number of students when tutorials were initiated to replace the "Dies" lost to academic measures.

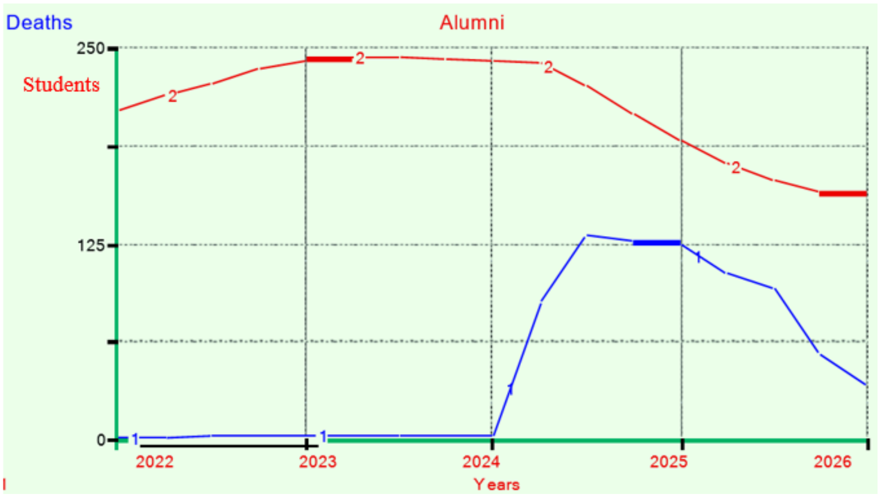


Figure 4. Sample results of graduating students vs. graduates

At-risk students, of which there is a drop in the number of students, and graduates who are then baccalaureate degree holders cause a significant drop in the student population. Also, with the oddity that the number of students at academic risk is higher than graduates, this indicates that professors are more focused on leveling students who are at risk rather than thesis advising. Figure 5 shows that the main concern of university administration should be to avoid a drop in the student body as a consequence of the large number of Academically At-Risk students expected to graduate without a degree in the years 2022, 2023.

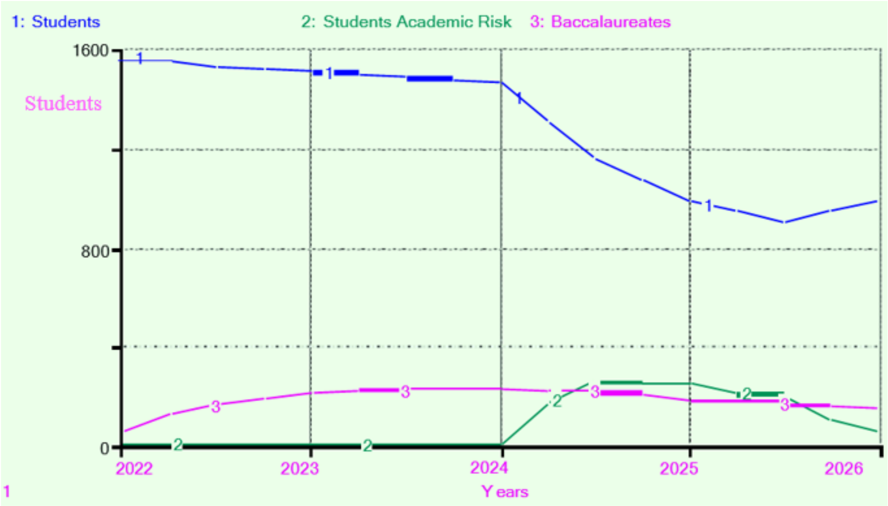


Figure 5. Sample results of good and average students-students at academic risk

Figure 6 shows the three types of graduates and the percentage of those who do not graduate and are therefore referred to as "old graduates". Graduates are not particularly motivated to complete their degrees through research and this lack of interest is reflected in the low average completion rates (7%) between 2022 and 2023; this indicates a systemic and institutional failure in engineering education. However, between 2023 and 2026, the number of research-based degrees (dissertations) awarded is expected to increase by 50%, which is a positive sign to engage universities in becoming research leaders.

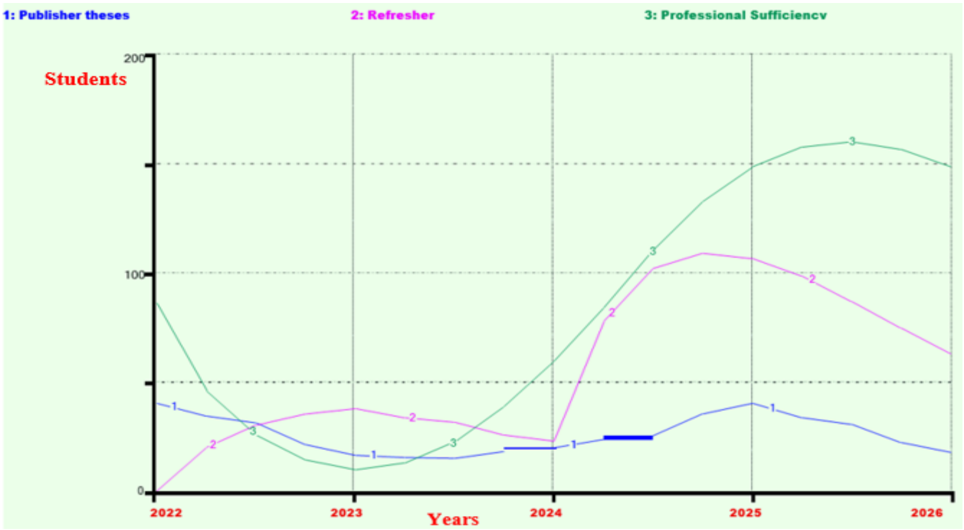


Figure 6. Published engineering thesis students in the institutional repository

## 5. CONCLUSION

In conclusion, the SD modeling helped to have a much better vision of the students with retention, especially in the engineering career. In this way, a tutoring proposal was provided to encourage students to continue their studies, model from 2022 to 2026. Thanks to the modeling, research degrees will be encouraged, reaching a 50% participation rate. This increase is a positive indicator encouraging universities to become research protagonists. The method used was SD, which consists of two diagrams, causal and Forrester. Also, with the help of Vensim software, it was possible to model the retention of engineering students. A limitation of the research work is that it was not possible to contact all the students to interview on the impact of tutoring on the retention of engineering students. In future work, it is suggested to complement this with a worldwide study on the impact of tutoring in universities. Also, to perform modeling with other software such as Stella and Dinamo.

## ACKNOWLEDGEMENTS

Thank everyone who made the research a reality for their support.

## REFERENCES


[1] M. Tight, "Student retention and engagement in higher education," *Journal of Further and Higher Education*, vol. 44, no. 5, pp. 689–704, May 2020, doi: 10.1080/0309877X.2019.1576860.

[2] P. S. Muljana and T. Luo, "Factors contributing to student retention in online learning and recommended strategies for improvement: a systematic literature review," *Journal of Information Technology Education: Research*, vol. 18, pp. 019–057, 2019, doi: 10.28945/4182.

[3] C. Dewberry and D. J. R. Jackson, "An application of the theory of planned behavior to student retention," *Journal of Vocational Behavior*, vol. 107, pp. 100–110, Aug. 2018, doi: 10.1016/j.jvb.2018.03.005.

[4] I. Godfrey, L. Rutledge, A. Mowdood, J. Reed, S. Bigler, and C. Soehner, "Supporting student retention and success: including family areas in an academic library," *portal: Libraries and the Academy*, vol. 17, no. 2, pp. 375–388, 2017, doi: 10.1353/pla.2017.0023.

[5] J. E. Nieuwoudt and M. L. Pedler, "Student retention in higher education: why students choose to remain at university," *Journal of College Student Retention: Research, Theory & Practice*, vol. 25, no. 2, pp. 326–349, Aug. 2023, doi: 10.1177/1521025120985228.

[6] A. Dixon, N. A. Silva, A. Sotayo, and C. A. Mazzola, "Female medical student retention in neurosurgery: a multifaceted approach," *World Neurosurgery*, vol. 122, pp. 245–251, Feb. 2019, doi: 10.1016/j.wneu.2018.10.166.

[7] S. A. Barbera, S. D. Berkshire, C. B. Boronat, and M. H. Kennedy, "Review of undergraduate student retention and graduation since 2010: patterns, predictions, and recommendations for 2020," *Journal of College Student Retention: Research, Theory & Practice*, vol. 22, no. 2, pp. 227–250, Aug. 2020, doi: 10.1177/1521025117738233.

[8] M. T. Alasaady, T. N. M. Aris, N. M. Sharef, and H. Hamdan, "A proposed approach for diabetes diagnosis using neuro-fuzzy technique," *Bulletin of Electrical Engineering and Informatics*, vol. 11, no. 6, pp. 3590–3597, Dec. 2022, doi: 10.11591/eei.v11i6.4269.

[9] M. N. Giannakos, I. O. Pappas, L. Jaccheri, and D. G. Sampson, "Understanding student retention in computer science education: the role of environment, gains, barriers and usefulness," *Education and Information Technologies*, vol. 22, no. 5, pp. 2365–2382, 2017, doi: 10.1007/s10639-016-9538-1.

[10] J. Roberts, "Professional staff contributions to student retention and success in higher education," *Journal of Higher Education Policy and Management*, vol. 40, no. 2, pp. 140–153, Mar. 2018, doi: 10.1080/1360080X.2018.1428409.

[11] S. L. Britt, D. A. Ammerman, S. F. Barrett, and S. Jones, "Student Loans, Financial Stress, and College Student Retention," *Journal of Student Financial Aid*, vol. 47, no. 1, pp. 25–37, 2017.

[12] K. Umam, M. Fachri, F. Nugroho, S. M. S. Nugroho, and M. Hariadi, "Serious game self-regulation using human-like agents to visualize students engagement base on crowd," *Bulletin of Electrical Engineering and Informatics*, vol. 11, no. 5, pp. 2717–2726, Oct. 2022, doi: 10.11591/eei.v11i5.3780.

[13] D. Byrne and S. McCoy, "Student Retention in Higher Education," *Economic Insights on Higher Education Policy in Ireland: Evidence from a Public System*, pp. 111–141, 2017.

[14] D. B. Monaghan and O. K. Sommers, "And now for some good news: trends in student retention at community colleges," *Research in Higher Education*, vol. 63, no. 3, pp. 425–452, 2022, doi: 10.1007/s11162-021-09656-6.

[15] A. F. Z. Abidin *et al.*, "Adaboost-multilayer perceptron to predict the student's performance in software engineering," *Bulletin of Electrical Engineering and Informatics*, vol. 8, no. 4, pp. 1556–1562, 2019, doi: 10.11591/eei.v8i4.1923.

[16] D. Aggarwal, S. Mittal, and V. Bali, "Significance of Non-Academic Parameters for Predicting Student Performance Using Ensemble Learning Techniques," *International Journal of System Dynamics Applications*, vol. 10, no. 3, pp. 38–49, 2021, doi: 10.4018/ijsda.2021070103.

[17] J. M. Ortiz-Lozano, A. Rua-Vieites, P. Bilbao-Calabuig, and M. Casadesús-Fa, "University student retention: Best time and data to identify undergraduate students at risk of dropout," *Innovations in Education and Teaching International*, vol. 57, no. 1, pp. 74–85, Jan. 2020, doi: 10.1080/14703297.2018.1502090.

[18] A. Smith, E. Aoki, M. Ghandi, J. Burek, C. Thompson, and K. Chandra, "Human balance models for engineering education: an innovative graduate co-creation project," *ASEE Annual Conference and Exposition, Conference Proceedings*, 2023, doi: 10.18260/1-2--43399.

[19] A. A. Tako and S. Robinson, "Comparing discrete-event simulation and system dynamics: Users' perceptions," *Journal of the Operational Research Society*, vol. 60, no. 3, pp. 296–312, 2009, doi: 10.1057/palgrave.jors.2602566.

[20] M. A. Prada *et al.*, "Educational data mining for tutoring support in higher education: a web-based tool case study in engineering degrees," *IEEE Access*, vol. 8, pp. 212818–212836, 2020, doi: 10.1109/ACCESS.2020.3040858.

[21] A. Drago, D. C. Rheinheimer, and T. N. Detweiler, "Effects of locus of control, academic self-efficacy, and tutoring on academic performance," *Journal of College Student Retention: Research, Theory and Practice*, vol. 19, no. 4, pp. 433–451, 2018, doi: 10.1177/1521025116645602.

[22] R. Setiawan, A. Aprillia, and N. Magdalena, "Analysis of antecedent factors in academic achievement and student retention," *Asian Association of Open Universities Journal*, vol. 15, no. 1, pp. 37–47, 2020, doi: 10.1108/AAOUJ-09-2019-0043.

[23] M. Destin, C. Castillo, and L. Meissner, "A field experiment demonstrates near peer mentorship as an effective support for student persistence," *Basic and Applied Social Psychology*, vol. 40, no. 5, pp. 269–278, 2018, doi: 10.1080/01973533.2018.1485101.

[24] J. Zhao *et al.*, "Power system dynamic state estimation: motivations, definitions, methodologies, and future work," *IEEE Transactions on Power Systems*, vol. 34, no. 4, pp. 3188–3198, 2019, doi: 10.1109/TPWRS.2019.2894769.

[25] M. G. Retuerto, D. Y. Espinoza, and L. Andrade-Arenas, "System dynamics modeling for solid waste management in Lima Peru," *International Journal of Advanced Computer Science and Applications*, vol. 12, no. 7, pp. 537–542, 2021, doi: 10.14569/IJACSA.2021.0120762.

[26] J. A. De Vinatea Ramírez, "System dynamics model to predict the effect of tutoring on the population of students at risk of academic dropout from the faculty of industrial and systems engineering of the national university of engineering, (in Spanish: Modelo de dinámica de sistemas para predecir el efecto de las tutorías en la población de alumnos en riesgo de deserción académica de la Facultad de Ingeniería Industrial y de Sistemas de la Universidad Nacional de Ingeniería)," Universidad Nacional Jorge Basadre Grohmann, 2019.

[27] B. K. Bala, F. M. Arshad, and K. M. Noh, *System dynamics*. Singapore: Springer Singapore, 2017, doi: 10.1007/978-981-10-2045-2.

## BIOGRAPHIES OF AUTHORS

**Laberiano Andrade-Arenas** is Doctor in Systems and Computer Engineering. Master in Systems Engineering. Graduated from the Master's Degree in University Teaching. Graduated from the Master's degree in accreditation and evaluation of educational quality. Systems Engineer. ITILV3 Fundamentals International Course (Zonngo-Peru/IMLAD-Mexico). Scrum fundamentals certified, Research Professor with publications in SCOPUS indexed journals. He has extensive experience in the University Chair in face-to-face and blended classes at different undergraduate and postgraduate universities in Lima. He can be contacted at email: landrade@uch.edu.pe.

**Margarita Giraldo Retuerto** is a Systems and Computer Engineering, researcher at the Faculty of Science and Engineering of the University of Sciences and Humanities, with publications in journals indexed in Web of Science and Scopus. She is focused on mobile applications, systems design, and machine learning. She can be contacted at email: margiraldor@uch.pe.

**Cesar Yactayo Arias** professional in administration and Master's in university teaching. Extensive teaching experience in higher education. In addition, experience in educational management. Doctoral study in administration. He can be contacted at email: cyactayo@continental.edu.pe.