

Preventive model to minimize students at academic risk for first-year college courses

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Abstract. The risk indicators of a student who is just starting his university studies are relevant to avoid a possible desertion and abandonment in a short term. A preventive model is presented that minimizes the percentage of students at academic risk in the first year of university studies, in the subject of Initial Programming. This work develops an empirical-analytical research methodology with a longitudinal and quantitative approach. The data used are the final grades of 360 students of nine courses of Initial Programming during three consecutive periods, from October 2021 to March 2022, from April to September 2022, and from October 2022 to March 2023, who used a preventive model for the academic support of first year students in the Engineering Careers of the Salesian Polytechnic University in the city of Guayaquil, Ecuador. The percentage of approved students reached 85% in the third period, an improvement of 8%. It is evident that a structural integration of teachers and students in relation to an ecosystem of digital didactic resources achieves the expected learning results and minimizes the percentage of students at academic risk.

Keywords: Dropping out of higher education, academic risk, interruption of studies, preventive model.

1 Introduction

The COVID-19 pandemic has opened up new possibilities for improving higher education with the support of strategies that prevent students from dropping out of a course in the first years of study, where more attention is needed (Radunzel, 2018). The risk indicators of a student who is just starting are of relevant importance to avoid a possible dropout and abandonment in the short term (Amaechi et al., 2022; Casanova et al., 2022; Geisler et al., 2023).

In addition, the transition from a secondary to a higher education ecosystem will depend on a set of conditions established by the educational institution to accommodate students from different academic situations and to carry out an integrated leveling with an effective content planning (Casanova et al., 2022; Gumennykova et al., 2022; Knight et al., 2022).

2 Theoretical Framework

The adaptation of strategies that involve a structural plan from the planning of content, the selection of teachers and the use of a virtual learning environment (VLE) is conducive to the effective development of a proven teaching and learning process (A Cedeño-Tello & Llerena-Izquierdo, 2023; Alicia Cedeño-Tello & Llerena-Izquierdo, 2023).

Determining the indicators of risk situations for a teacher of a specific course leads to a capacity to generate learning data to know the different deficient instances of the student within a set of observable activities, tangible in with the VLE data and observable within the classroom, the interaction with classmates and with the members of the institution that provide the welcome in planned spaces (laboratories and tutorials) (Figueroa-Cañas & Sancho-Vinuesa, 2021; Knight et al., 2022; Weng et al., 2021).

This paper presents a preventive model that minimizes the percentage of students at academic risk in first-year university subjects, specifically in the technical subject of Initial Programming.

3 Methods

This work develops an empirical-analytical research methodology with a longitudinal and quantitative approach. It uses as data the final grades of approximately 360 students of nine courses of Initial Programming during three consecutive periods (Academic period 59 from October 2021 to March 2022, Academic period 60 from April to September 2022, Academic period 61 from October 2022 to March 2023) that used a preventive model for the academic support of first year students in the Engineering Careers of the Salesian Polytechnic University in the city of Guayaquil, Ecuador.

The model is based on a structure from Academic Coordination (Universidad Politécnica Salesiana, 2020) which involves a team of professors with empathy and working skills with first year students, a set of upper cycle students trained for lab work and tutorials, and a set of digital resources with practical learning guides for autonomous work and lab work supported by a VLE and academic social networks (Llerena-Izquierdo & Ayala-Carabajo, 2021; Llerena Izquierdo, 2023)(see Fig. 1).

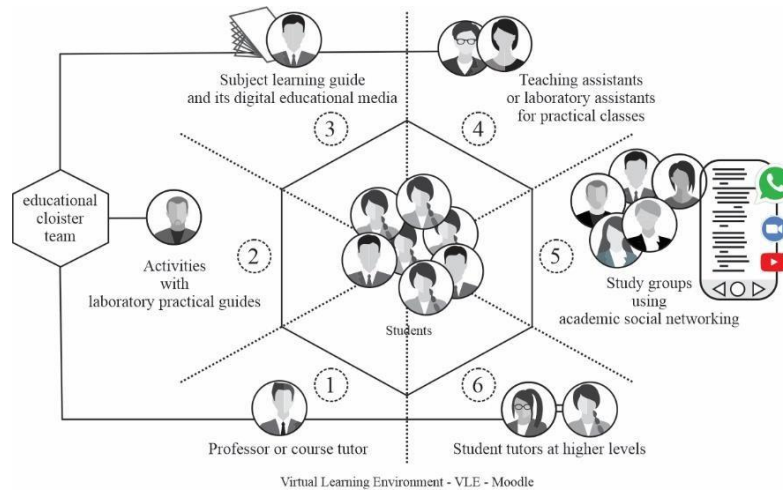


Fig. 1. Preventive model integrating the VLE, academic social networks, students, and faculty of the faculty educational cloister team.

4 Results

The results of the data collected in academic periods 59, 60 and 61 reflect that the preventive model applied in the subjects of Initial Programming in engineering majors has had a positive effect on the percentage of student performance in the nine participating courses (see Fig. 2).

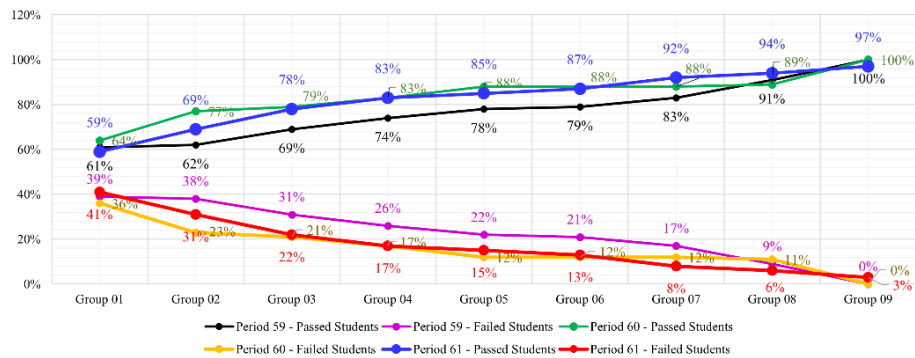


Fig. 2. Percentage of passing and failing students by course during the 59th, 60th and 61st academic periods, respectively.

For October 2021 to March 2022 (Academic Period 59), the percentage of students passing reaches 77%, while the application of the pre-encouragement model to the following period (60) achieves 84%, and in the last recent period (61) improves to

85%. The percentage of loss from 7% to 8% since the use of the proposed model began (see Fig. 3).

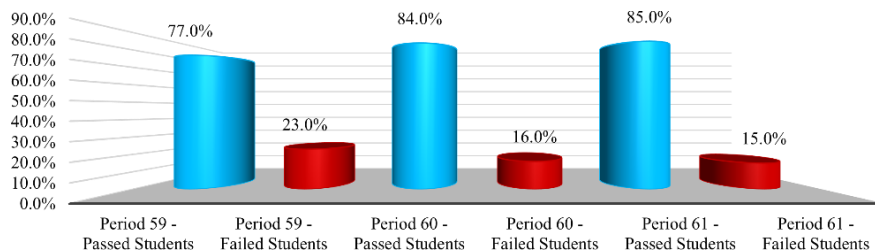


Fig. 3. Percentage of students who passed and failed during the 59th, 60th and 61st academic periods respectively.

5 Discussion

It is discussed that the model presented has the direct intervention of the team of teachers involved as tutors of a similar course and avoids the use of algorithms that predict a risk situation by classifying the student and generating possible beliefs in the teaching team (Nabil et al., 2021; Talsma et al., 2021) and depersonalize the teaching process that is based on the approach to students. Involving machine learning techniques is still questioned because of the multiple factors that can affect a student's performance and their relationship with the tools that generate data for reliable prediction (Kuzilek et al., 2021; Tamada et al., 2022).

6 Conclusions

Educational efforts in higher education to discover, assist and prevent students from finding themselves in a situation of academic risk are achieved when there is a model that interconnects spaces and people that evidence an anomalous situation. This work presents an effective model in the context of students of the first year of engineering studies in the subject of initial programming that contemplates a structural integration of teachers and students of higher education in relation to an ecosystem of digital teaching resources that accompany students to achieve the expected learning outcomes and minimize the percentage of students at academic risk and avoid a situation of dropout or desertion. The results exceed 80% effectiveness, a value that exceeds the authors' expectations.

7 Limitations and Future Research

The limitations found are aimed at supporting the use of machine learning algorithms within the courses offered due to the computational cost (C.-H. Chen et al., 2021;

Guerrero-Roldán et al., 2021) and to the available resources of the higher education institution's computer services (Naseem et al., 2022; Parhizkar et al., 2023). Future work is aimed at leveraging a model through web tools and services using learning analytics and incorporating custom machine learning algorithms (Y. Chen & Zhai, 2023; Llerena-Izquierdo et al., 2022).

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