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ORIGINAL

Model for Curriculum Analysis Based on Process and Data Mining

Modelo para el análisis curricular basado en la minería de procesos y datos

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ABSTRACT

The article addressed the importance of curricular aspects in academic management, highlighting its role in learning and optimizing the curriculum. Student performance was analyzed by studying enrollment, academic progress and risk factors such as dropout, poor performance and failure of subjects. The application of process mining and data analysis made it possible to identify hidden patterns, facilitating pedagogical interventions to improve educational quality. Key concepts were defined, differentiating between curricular management and data analysis. At the curricular level, successful graduation, student dropout, and strategic curriculum planning were detailed. Regarding data management, predictive analytics was highlighted as a tool for decision-making in higher education. The study used a quantitative approach, structured in three phases: exploration, design and validation. In the exploratory phase, previous studies on graduation, curricular management and dropout were reviewed. During the design phase, process mining techniques were integrated to evaluate the student trajectory and detect bottlenecks. Finally, in the validation phase, the model was applied in an academic program, demonstrating its effectiveness in detecting curricular problems. The results indicated that the CRISP-DM methodology was the most used in educational data mining, providing a structured framework for the identification and resolution of academic problems.

Keywords: Process Mining; Curriculum Management; Data Analytics.

RESUMEN

El artículo abordó la importancia de los aspectos curriculares en la gestión académica, destacando su papel en el aprendizaje y la optimización del plan de estudios. Se analizó el desempeño estudiantil mediante el estudio de la matrícula, el avance académico y factores de riesgo como la deserción, el bajo rendimiento y la reprobación de asignaturas. La aplicación de minería de procesos y análisis de datos permitió identificar patrones ocultos, facilitando intervenciones pedagógicas para mejorar la calidad educativa. Se definieron conceptos clave, diferenciando entre gestión curricular y análisis de datos. En el ámbito curricular, se detalló la graduación exitosa, la deserción estudiantil y la planificación estratégica del plan de estudios. En cuanto a la gestión de datos, se resaltó la analítica predictiva como herramienta para la toma de decisiones en educación superior. El estudio utilizó un enfoque cuantitativo, estructurado en tres fases: exploración, diseño y validación. En la fase exploratoria, se revisaron estudios previos sobre graduación, gestión curricular y deserción. Durante la fase de diseño, se integraron técnicas de minería de procesos para evaluar la trayectoria estudiantil y detectar cuellos de botella. Finalmente, en la fase de validación, se aplicó el modelo en un programa académico, demostrando su efectividad en la detección de problemas curriculares. Los resultados indicaron que la metodología CRISP-DM fue la más utilizada en la minería de datos educativa, proporcionando un marco estructurado para la identificación y resolución de problemas académicos.

Palabras clave: Minería de Procesos; Gestión Curricular; Analítica de Datos.

INTRODUCTION

Curricular aspects are fundamental elements that support learning in a training process. Therefore, it is essential to analyze students' academic performance based on their behavior in enrollment and progress through the curriculum.

Analysis of the curriculum allows us to identify patterns that facilitate the early detection of risk factors associated with different variables inherent to the curricular management of a program, such as student dropout, low academic performance, successful graduation, and subjects with the highest failure rates, among others. As mentioned, [1] these factors lead to adjustments to curricular routes, changes in pedagogical interventions, and improvements in the effectiveness of teaching and learning processes. This contributes to student retention and optimizes educational resources, raising academic quality.

On the other hand, process mining and data analysis play a crucial role in identifying hidden patterns and developing assertive improvement plans, given that the behavior of processes and the data they generate are analyzed. Process mining is a discipline that combines tools and techniques based on data mining to analyze business processes whose records of actual execution events are available in information systems. [2]

However, process mining applied to the curriculum, taking the study plan under analysis, answers key questions: How are academic processes being executed in reality? And where are the bottlenecks? These questions are crucial to identifying the critical points within the academic trajectory that affect students' progress in the program with the aim of achieving successful graduation.

Likewise, data analytics asks the right questions to generate forecasts and predictive models of students' academic performance. According to authors, [3] data analytics is the process by which institutions can analyze the present and the past and build models that allow them to predict the future and take proactive measures to improve the program's quality.

Therefore, the article proposes the design and validation of a comprehensive model that combines data analytics and process mining techniques to offer a practical and effective solution in the monitoring of the curriculum and thus facilitate actions for improvement in curriculum management that serves as input for making significant changes in the curriculum, responding to the needs of the student and the challenges of the professional environment. Among the factors analyzed are curricular routes, conformity analysis, and bottlenecks that allow for the study of variables such as successful graduation, student dropout, and subjects with the highest failure rates, among others.

Related Concepts

The article identifies two thematic domains that interact for the development of the Curriculum Management Model based on the analysis of data and processes. To this end, concepts are defined in terms of their association with the curriculum and, secondly, those related to the discipline of data management.

Curriculum

- Curriculum Management: refers to the set of decisions, processes and actions that allow for the planning, implementation, evaluation and adjustment of educational programs in order to ensure quality in teaching and learning.[4]
- Successful Graduation: refers to the completion of an academic program by students within a specified time and in compliance with the requirements established by the educational institution.[5]
- Student dropout: a complex phenomenon that encompasses all partial or total abandonment of an academic program.[6]
- Curriculum: the result of strategic planning of the curriculum that integrates the distribution of subjects based on the logic for the development of competencies, establishing prerequisites that ensure that students have the prior knowledge necessary to take more advanced subjects.[3]

Data management

- Análisis de datos: es el proceso mediante el cual las instituciones pueden analizar no solo el presente y el pasado, sino también construir modelos que permitan predecir el futuro.[3]
- Análisis de procesos: La minería de procesos es una disciplina que combina herramientas y técnicas basadas en la minería de datos para analizar los procesos de negocio, cuyo registro de eventos de ejecución real se encuentra disponible en sistemas de información.[2]

METHOD

The study's methodological approach is developed under a quantitative paradigm, [7] allowing the collection and analysis of large volumes of data to identify patterns in student dropout and graduation. A deductive method is used for hypothesis formulation and verification.

The study began with extracting reports from the institution's Academic Information System and obtaining historical data on student cohorts, academic records, and enrolment status. In parallel, a systematic review of the literature was carried out to identify the key factors influencing dropout and graduation in engineering programs, establishing the theoretical basis for reviewing previous research in the university context. With this information, we proceeded to the design phase of the Curriculum Management Model, which integrates process mining and data analysis techniques to visualize academic trajectories and detect patterns of student behavior. To do this, we used tools such as Bizagi for process modeling, Power BI for visual analysis, and Python to generate predictive models, allowing us to comprehensively address the identified dropout and graduation issues. Subsequently, in the validation phase, the model was implemented through a case study in the academic program of Software Engineering at TdeA, using an initial database of 32,224 records, which, after a rigorous cleaning and debugging process, was reduced to a final set of 2,234 reliable records. This analysis, which covered the 2018-1 and 2018-2 semesters, facilitated a longitudinal comparison of academic indicators through the management, analysis, and visualization of data using Python, Power Automate, and Power BI tools. During this phase, relevant records were filtered to identify key academic statuses (enrolments, withdrawals, and approvals). Additional variables were incorporated, such as retention and dropout rates, providing a complete view of academic performance. Finally, integrating these methods allowed for a comprehensive validation of the model, demonstrating its ability to detect patterns and optimize the curriculum throughout the different phases of the curricular analysis.

To guarantee the replicability of the present study, various strategies have been adopted in line with the best practices recommended in the literature [8] and [9]. Firstly, the data analysis has been documented in detail, avoiding selecting variables solely based on arbitrary significance thresholds and instead basing decisions on robust statistical criteria and the educational context. In addition, multiple alternative predictive models have been developed to evaluate different scenarios. In this case, one model was created to improve the validity of the findings, following approaches such as the information criterion. Python scripts have also been generated for data processing and analysis, which can be reused by other researchers interested in replicating the study in different educational contexts.

The availability of the original data, institutional confidentiality permitting, and the documentation of each methodological step contribute to the transparency of the study. Finally, open access to the results is encouraged, as is academic discussion on replicability in educational research, thus strengthening the reliability and applicability of the proposed model in other academic programs and universities.

RESULTS

The results obtained from each of the phases of the model are presented below.

A. Exploration phase

We present works that instantiate data analysis applied to the educational context. We find that the works focus on the curricular sphere in three [3] aspects: a) successful graduation, b) curricular management, and c) student dropout. These are described below:

Table 1. Research categories

Category	Job Description
Successful graduation	According to [5] develops the Academic Integration Model. In accordance with [10] analyzes the individual and contextual factors that influence successful graduation.
Gestión curricular	In line with the authors' approach [4] Examines the importance of strategic curriculum planning. The authors [11] Discuss the evaluation and continuous adjustment of the curriculum as a collaborative process.
Student dropout	According to [10], they propose a multidimensional view of dropout. The author [5] details the academic, social and economic causes of dropout. In line with the work carried out by [12], they explain the analysis of the factors that contribute to the design of strategies to improve student retention.

The analysis shows that the most commonly used methodological framework in data mining projects is CRISP-DM (Cross Industry Standard Process for Data Mining), which provides six phases for its development:

business understanding, data understanding, data preparation, modeling, evaluation and implementation, as detailed [13]

This model provides a systematic structure that facilitates the application of process mining and data analytics techniques, allowing for the precise identification of critical points in an academic context, as well as the application of corrective measures.

B. Design Phase

The model analyses the behaviour of the curriculum in the academic programme of higher education to establish, through student progress, the causes and situations that affect the curricular development of the programme. The variables analysed include student dropout and successful graduation, through process analysis techniques, which, as mentioned [2], are indispensable for the analysis of curricular processes. Likewise, conformity and bottleneck analyses are implemented that are presented in the curricular routes that the curriculum of an academic program presents.

The CRISP-DM methodology is taken as a reference to structure the model, structuring the model in five phases that allow for a comprehensive understanding of the process analysis applied to the academic program based on the curriculum.

In the following figure, you can see the methodology of the curricular analysis.

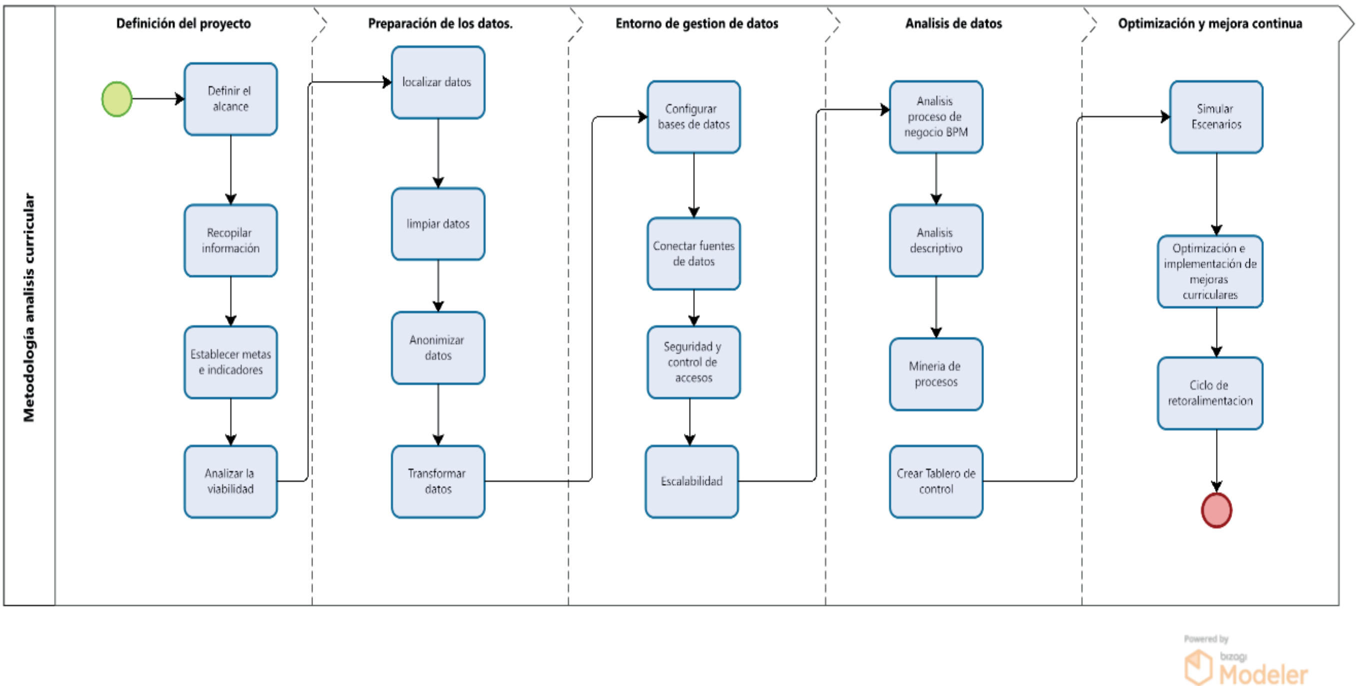

Figure 1. Model for analyzing curricular processes

Project definition: Objectives, scope of analysis, and key performance indicators (KPIs) aligned with the institution were established. The curriculum was modeled in Bizagi BPM to visualize academic paths, interdependencies between subjects, and possible bottlenecks affecting student progress. First, the data was extracted, transformed, and uploaded using Power Query and Power Automate, hosting the academic database in Azure or SharePoint. Then, using Power Automate, the process routes followed by students throughout their educational careers were analyzed, identifying the most frequent sequences of events and significant deviations. Subsequently, a root cause analysis was conducted to detect the most critical problems and deviations, examining the associated data and events in detail. Finally, the results were presented through reports on the same platform, highlighting the proposed improvements and key performance indicators. These indicators were measured using quantitative metrics (for example, retention rates and course completion times) obtained directly from the academic database and cross-checked with official institutional sources, thus guaranteeing the reliability of the information.

The KPIs were measured using quantitative metrics based on institutional data sources, ensuring an accurate analysis and adjustments based on the findings obtained, as shown in the following table:

Table 2. KPIs for analyzing the success of an academic program

Item	Indicator	Description	Calculation	Importance
1	Pass rate	It measures the percentage of students who pass a subject	(Number of students who pass a subject / Total number of students enrolled) * 100	It assesses whether students are understanding the content of the subjects and are meeting the academic requirements.
2	Dropout rate	It measures the percentage of students who abandon the academic program before finishing their studies.	(Number of students who drop out of the program / Total number of students enrolled) * 100	Identify the causes that lead students to abandon the program.
3	Average time to graduation	Calculate the time it takes a student to complete the academic program from admission to graduation.	∑ (Time taken by each student to graduate) / Total number of students who graduated	It evaluates the efficiency of the curricular process and whether students manage to complete the program in the expected time.
4	Student satisfaction	It determines the level of student satisfaction with aspects of the academic program.	Weighted average of responses in student satisfaction surveys.	It reflects on whether the program meets the expectations and needs of the students.
5	Retention rate	It measures the percentage of students who continue their studies in the program after each year.	(Number of students continuing their studies in the next year / Total number of students enrolled) * 100	It indicates whether the students are committed to the program and whether they receive adequate support.
6	Subject repetition rate	Calculate the percentage of students who have to repeat a subject.	(Number of students repeating a subject / Total number of students enrolled) * 100	It reveals whether there are problems in teaching or excessive difficulty in the contents.
7	Use of educational resources	It measures the frequency with which students access and use educational resources.	Record of access to libraries, learning platforms or laboratories.	It allows us to evaluate access to educational resources and their relationship with academic performance.
8	Success rate in prerequisites	It determines the percentage of students who successfully pass the courses that are prerequisites for other subjects.	(Number of students who pass the prerequisites / Total number of students enrolled) * 100	It assesses whether previous courses are designed appropriately and whether students are well prepared for more advanced subjects.
9	Cumulative academic progress	Checks the percentage of credits or subjects completed in relation to the total required for graduation.	(Number of credits completed / Total number of credits needed to graduate) * 100	It monitors the general progress of students in the program, identifying whether they are progressing as planned.
10	Subject dropout rate	It measures the percentage of students who abandon a subject before finishing it.	(Number of students who cancel a course / Total number of students enrolled) * 100	Identify subjects with high dropout rates in order to adjust their structure or academic support.
11	Participation in extracurricular activities	Assess the percentage of students who participate in extracurricular activities related to academic development	(Number of students participating in extracurricular activities / Total number of enrolled students) * 100	It evaluates the relationship between participation in complementary activities and academic performance.
12	Access to tutorials and mentoring	It measures the frequency with which students access academic mentoring services.	Number of students accessing tutorials / Total number of students enrolled in the program	It determines whether students are using the available support resources and whether these have a positive impact on their performance.
13	Rate of students with overdue credits	It determines the percentage of students who have not completed the credits corresponding to their academic semester	(Number of students with credits pending from previous semesters / Total number of students at that level) * 100	It detects problems related to delays in the accumulation of credits, which can affect graduation times.

The curriculum consists of 10 levels with a progressively complex system of prerequisites, where the dependency between subjects intensifies from the third semester onwards.

Data preparation: Data is located, cleaned and transformed for analysis, ensuring quality, anonymization and compatibility with analytical tools.

Data management: A secure database is configured and integrated into platforms such as Azure or SharePoint, guaranteeing scalability and information protection.

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Analysis and visualization: Academic performance patterns are identified with tools such as Power BI and Bizagi, optimizing curricular paths through interactive dashboards and process mining.

Predictive models and optimization: A machine learning model is implemented with Python to predict academic dropout and propose improvements to the curriculum. A feedback cycle based on a Gantt chart allows for continuous adjustments.

C. Validation Phase

The results of the study are based on the implementation of a curriculum management model based on data analysis and process mining. It presents a case study analyzing the Software Engineering program at Tecnológico de Antioquia - University Institution (TdeA). The main findings are presented below:

Table 3. Analysis by category

Category of analysis	Description	Main findings	Implications
Student dropout	Factors that contribute to students abandoning the academic program.	- High failure rate in key subjects. - Bottlenecks in second and third semesters.	- Need to redesign the curriculum to reduce complexity at critical stages. - Implementation of strategies such as personalized tutoring to improve retention.
Successful graduation	Strategies and conditions that enable students to complete their academic program on time.	Reduction of the average time to graduation by one semester.	Optimization of academic pathways to ensure smooth progress. Importance of making prerequisites more flexible to adapt to the needs of students.
Management of the academic curriculum	Planning and continuous adjustment of the curriculum to improve performance and retention.	- Improvement in the sequencing of subjects. - Identification of efficient curricular routes. - Integration of data visualization and analysis tools.	- Facilitate data-based decision making by administrators and teachers. - Promote the periodic updating of the curriculum to adapt to academic and labor trends.
Process mining applied to the curriculum	Analysis of academic pathways and student trajectories using advanced tools such as	- Identification of critical points in the students' progress.	- Use of advanced technologies such as Power Automate, to model and analyze data. - Application of simulations to predict and mitigate problems before they affect students.
Descriptive analysis with Python	Predictive analysis of risk factors related to dropout.	Identification of students at risk through patterns detected in historical data.	Applying Machine Learning, a predictive model was created using Python that allows preventive strategies to be planned.
Key performance indicators (KPIs)	Metrics used to evaluate the effectiveness of the curriculum management model.	- Increase in the retention and approval rate. - Reduction in the rates of repeating subjects.	- KPIs allow for continuous monitoring of institutional progress. - Their integration into control panels facilitates communication and coordinated action between the different actors in the program.
Impact of intervention strategies	Effectiveness of the actions implemented to mitigate dropout and improve performance.	- 10 % reduction in dropout rates. - Greater acceptance among students of the strategies implemented.	- Personalized and specific interventions are key to addressing the multidimensional factors of dropout. - Importance of conducting pilot tests and adjusting strategies based on the results obtained.
Pensum as a business process	Analysis of the academic curriculum as a business process focused on efficiency and sustainability.	Optimization of content, elimination of redundancies and alignment with the demands of the labor market.	Implementation of a systemic approach to designing the curriculum, taking into account institutional objectives and the graduate profile.

Each category highlights a key aspect of the problem addressed, and the results obtained in this case agree with the scientific literature that highlights the importance of flexible and data-based curriculum management in mitigating dropout and promoting successful graduation in higher education. Various research studies have shown that factors such as academic and social integration, institutional support, the personalization of curricular pathways, and the use of advanced analytical tools play a fundamental role in student retention.

[10] emphasizes that the academic and social integration of the student is an essential factor for their permanence in the university. His theory of student development suggests that active participation in educational and extracurricular experiences fosters a sense of belonging that reduces dropout risk. In line with this approach, [5] highlights the need to rethink institutional actions to increase the completion of studies,

suggesting that student dropout not only responds to individual factors but also to institutional structure and support failures. In this sense, universities must design strategies that not only respond to academic problems but also to psychosocial and economic factors that affect the continuity of students.

The use of predictive analytics tools has proven to be an effective strategy for improving student success, as it allows for the early identification of students at higher risk of dropping out. [14] Emphasizes that applying predictive models based on machine learning and data mining can provide key information for designing timely and personalized interventions. Meanwhile, [7] argues that robust quantitative analysis is vital for making informed decisions in academic management. Institutions can anticipate dropout patterns and adjust their retention strategies by processing historical student data.

Furthermore, [15] and [12] point out that developing personalized strategies and continuous monitoring throughout the academic trajectory are effective practices for increasing retention. The implementation of tutoring, mentoring programs, and academic advising has been shown to significantly impact reducing dropout rates, as they allow students to receive specific support according to their needs. In this context, the automation of early warning systems can facilitate the detection of academic and emotional difficulties, enabling proactive intervention by teachers and counselors.

On the other hand, the proposal to optimize the curriculum based on process mining and data analytics coincides with studies such as that of [16], which demonstrated how machine learning techniques can guide the creation of more efficient curricular routes. By analyzing students' academic progression and its relationship to performance in certain subjects, it is possible to adjust the study plan structure to minimize dropout and improve graduation rates. Likewise, [17] highlights using prediction models to anticipate the number of graduates, which allows institutions to plan resources better and optimize academic offerings.

Various researchers have pointed out the integration of academic analytics with decision-making in higher education. [18] argues that incorporating data analysis tools in university management can provide accurate information on retention and dropout trends, facilitating the design of more effective strategies. These tools can range from interactive dashboards to artificial intelligence systems that monitor student performance in real-time.

Finally, improving study plans and implementing timely intervention strategies can significantly reduce dropout rates in higher education institutions. Data-based curriculum management allows for greater flexibility in academic pathways, adapting the range of subjects on offer to the needs and profiles of students. In this sense, universities must adopt a student-centered approach, where educational innovation and institutional support are key pillars to guarantee retention and academic success.

Study limitations

Despite the relevant findings obtained in this research, it is necessary to consider a series of limitations that may influence the interpretation and generalization of the results:

One of the main limitations is the lack of data standardization. Due to the need to carry out a cleaning and filtering process, errors or biases may have occurred when eliminating duplicate or inconsistent records. This situation can affect the accuracy of the results and, therefore, the validity of the conclusions.

Variations in the curriculum (pensum) and the periodic change of curricula make it difficult to compare results longitudinally since subjects, prerequisites, and content can vary significantly from one cohort to another. This limits the possibility of establishing homogeneous dropout or graduation patterns over time.

Limited data sources: Sometimes, the information does not come from multiple data sources but from a single academic database or institutional repository. This restriction reduces the ability to cross-check the information with other sources that could enrich the analysis and reduce possible biases.

Security restrictions and access to information: When obtaining data, security measures may be put in place that prevent free access to certain repositories or databases. This can hinder the complete information collection, making it difficult for more exhaustive and detailed analysis. Furthermore, the presence of privacy policies can restrict the publication of specific sensitive data, limiting the scope of the study.

Technological resources and specialized knowledge: Not all institutions or researchers have the necessary technological resources, including analysis software, servers, process mining tools, or the specialized knowledge to handle large volumes of information. This can prevent the proposed methodology from being applied in other educational or professional contexts.

Possible biases in data handling: although the data is accurate, cleaning and selecting variables can introduce unintentional biases. However, these are significantly reduced when working with official institutional information and direct academic records, which gives the results more excellent reliability.

Suggestions for future research

The evidence gathered throughout this study indicates that the combination of process mining and data analysis can offer practical solutions to reduce student dropout and optimize curriculum management.

However, to maximize the potential of this approach, several lines of research and improvement are proposed, one of which is replicability in other programs and contexts; it would be valuable to replicate the proposed model in academic programs in different areas of knowledge for example, health sciences, social sciences or arts, to determine the robustness and generalizability of the results. Likewise, extending the application to institutions in different countries would make it possible to evaluate how cultural, normative, and economic factors influence the model's effectiveness, offering a broader comparative perspective.

One important suggestion would be to integrate socioeconomic and demographic variables, including economic and family factors, such as information related to the student's financial situation, the educational level of their parents, and the availability of scholarships or grants. This could provide a more complete picture of the reasons for dropout or academic progress.

The study methods could be analyzed to determine the differences between face-to-face, virtual, or hybrid students and help determine whether the teaching method affects the effectiveness of the model and the dropout rates.

Another aspect would be to delve deeper into mixed methodologies, including a qualitative approach combining data analysis with qualitative methodologies such as in-depth interviews or focus groups. These can reveal subjective aspects that are not reflected in numerical metrics, such as personal motivation, expectations, or perceptions about the quality of teaching.

For its part, the triangulation of information, which could contrast the quantitative results with the qualitative evidence, could strengthen the validity of the conclusions and offer a more comprehensive understanding of the dropout and graduation processes.

The optimization and evolution of predictive analytics with more advanced models, exploring deep learning algorithms or ensemble techniques to improve the accuracy of dropout prediction and the identification of academic risk profiles.

Continuous data updating: Given that curricula and cohorts evolve, it would be helpful to implement a constant monitoring system that dynamically adjusts predictive models as academic or administrative conditions change.

CONCLUSIONS

Discussion of the results obtained in this study reveals that the implementation of the model can impact curriculum management based on data analysis and process mining. One of the most significant findings is that, through implementation, it is possible to identify the factors contributing to student dropout, including high failure rates in key subjects, bottlenecks in the initial semesters, and limitations in the academic monitoring of students. These problems highlight the need for specific interventions that mitigate academic barriers and promote smoother progress throughout the program.

The analysis of academic trajectories allowed for the precise mapping of students' routes, identifying critical points in the curriculum where most of the difficulties are concentrated. For example, the second and third semesters have high rates of repetition and dropout, which leads to an accumulation of students and a saturation of resources at these stages.

Curricular management plays a fundamental role in this model's success. Strategic curriculum planning, based on data and an understanding of academic dynamics, can enable better subject sequencing and alignment of pedagogical objectives with the environment's needs. Process mining applied to academic pathways has been a key tool in understanding how students interact with the curriculum and what modifications can ensure a more effective learning experience.

The impact of the management model is not limited to academic performance; it can also encompass emotional and social aspects that affect the student experience. Integrating personalized interventions, such as tutoring and psychosocial support programs, has contributed to a more inclusive and equitable educational environment.

One of the most relevant findings is the model's capacity to adapt and scale to other academic programs. The approach's flexibility and foundation in universal technologies allow for its replication in different contexts, making it a valuable tool for institutions facing similar challenges. Furthermore, the constant evaluation of key performance indicators (KPIs) ensures that the model can be dynamically adjusted according to emerging needs.

It is important to point out that implementing this model also faces challenges. These include some actors' resistance to change, initial technological limitations, and the need for continuous staff training. Overcoming these barriers requires a comprehensive approach that combines training, effective communication, and committed leadership.

Finally, the findings highlight the effectiveness of the curriculum management model based on data analysis and processes that improve academic performance, reduce dropout rates, and optimize the educational experience. This model addresses specific problems of the software engineering program at Tecnológico de

Antioquia and offers a replicable roadmap for other institutions.

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