PREMUCC: Design proposal for a microservices architecture for the development of a context-aware dropout prediction system

PREMUCC: Propuesta de diseño de una arquitectura de microservicios para el desarrollo de un sistema de predicción de deserción escolar consciente del contexto

DOI: http://dx.doi.org/10.17981/ingecuc.20.2.2024.09

Scientific Research Article.
Date of Receipt: 17/08/2023 Date of Acceptance: 24/01/2024.

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To cite this paper:
L. Arenales-Gonzalez, J. Gonzalez-Gomez, & J. Saldana-Barrios, "PREMUCC: Design proposal for a microservices architecture for the development of a context-aware dropout prediction system," INGE CUC, vol. 20, no. 2, 2024. DOI: https://dx.doi.org/10.17981/ingecuc.20.2.2024.09

Abstract

Introduction--- This article presents the PREMUCC system, a proposal based on microservices to predict context-aware college dropout in higher education. Student attrition is a concerning issue addressed by this innovative solution, enabling personalized support and informed decision-making.

Objective--- The objective of the PREMUCC system is to anticipate university dropout through the use of machine learning techniques and a microservices architecture, providing personalized support to students and facilitating educational management.

Method--- The proposal for PREMUCC was based on analyzing dropout prediction systems and microservices architectures. Technologies and data analysis processes were identified to ensure system efficiency and accuracy.

Results--- The PREMUCC system integrates six microservices encompassing user authentication, previous studies analysis, psychological testing, grade tracking, financial evaluation, and the prediction system. Students access personalized information to improve their academic performance.

Conclusions--- The PREMUCC proposal represents a significant advancement in mitigating college dropout. Its focus on microservices and modern technologies enables closer tracking of each student's context, supporting informed decision-making. Its implementation could enhance the educational system, saving resources, time, and effort. It is proposed to strengthen the architecture and evaluate its effectiveness in real higher education settings.

Keywords--- School dropout; microservices; context-awareness; prediction; intelligent system.

Resumen

Introducción--- Este artículo presenta el sistema PREMUCC, una propuesta basada en microservicios para predecir la deserción escolar consciente del contexto en educación superior. La deserción estudiantil es una preocupante problemática que se aborda con esta innovadora solución, permitiendo un seguimiento personalizado y toma de decisiones informada.

Objetivo--- El objetivo del sistema PREMUCC es anticipar la deserción escolar universitaria mediante el uso de técnicas de aprendizaje de máquina y una arquitectura de microservicios, brindando apoyo personalizado a los estudiantes y facilitando la gestión educativa.

Metodología--- Se fundamentó la propuesta PREMUCC a partir de un análisis de sistemas de predicción de deserción y arquitecturas de microservicios. Se identificaron tecnologías y procesos de análisis de datos para garantizar la eficiencia y precisión del sistema.

Resultados--- El sistema PREMUCC integra seis microservicios que abarcan autenticación de usuarios, análisis de estudios previos, pruebas psicológicas, seguimiento de calificaciones, evaluación económica y el sistema de predicción. Los estudiantes acceden a información personalizada para mejorar su rendimiento académico.

Conclusiones--- La propuesta PREMUCC representa un avance significativo para mitigar la deserción escolar universitaria. Su enfoque en microservicios y tecnologías modernas permite un seguimiento más cercano al contexto de cada estudiante, respaldando la toma de decisiones informada. Su implementación puede mejorar el sistema educativo y ahorrar recursos, tiempo y esfuerzo. Se propone fortalecer la arquitectura y evaluar su efectividad en entornos reales de educación superior.

Palabras clave--- Deserción escolar; microservicios; conciencia de contexto; predicción; sistema inteligente.

I. INTRODUCTION

School dropout, also known as educational dropout or early school leaving, refers to the departure of students from the formal education system before obtaining the corresponding degree upon completion of their studies [1].

Authors like Vizcaino [2] and Tinto [3] agree that there is a high rate of early school dropout, which occurs at the end of the first year of studies and is closely related to difficulties in meeting academic demands.

Días, Ramírez, and McEdo [4] concur that socio-economic, personal, and family factors and personal and academic aspects can influence school dropout. Vanegas and Salazar [5] point out that in public universities, low averages in upper secondary education, marital status, and the need to start working are also factors that contribute to dropout.

It is crucial for educational institutions to thoroughly evaluate and analyze the circumstances and challenges each student faces, becoming aware of the context and environment in which the student is situated, and implementing preventive measures to avoid school dropout [6].

Artificial Intelligence (AI)-based prediction systems enable educational institutions to identify patterns and correlations in student data and their environment. These systems help identify students with a high risk of leaving their studies before they do, allowing for timely preventive measures to mitigate the risk and keep students engaged in their education.

Furthermore, ubiquitous learning (u-learning) can provide alternative educational opportunities for those who dropped out of school, such as online courses, mobile applications, and other digital resources. Ubiquitous learning allows the integration of diverse computing devices and communication technologies to facilitate the teaching-learning process and its analysis [7].

Considering the focus on ubiquitous learning, intelligent prediction systems, and the prospect of significant advancements in educational support tools, this study proposes the development of a context-aware school dropout prediction system using architectural patterns like microservices. The objective is to predict in a timely and accurate manner the percentage of a student's potential risk of school dropout by evaluating both personal data and their environment.

II. PROBLEM STATEMENT

School dropout is an issue that has significant repercussions on societal development, and intensifying efforts and research on this topic can help mitigate its effects. This has led to establishing projects like the Institute for Higher Education in Latin America and the Caribbean (IESALC) [8], which aimed to analyze the extent of university dropout in 15 participating countries. Similarly, the Regional Office of Education for Latin America and the Caribbean (ORELAC) states that "in the region, only one out of every ten students aged 25 to 29 had completed five years of higher education in 2010" [9].

In the Republic of Panama, the school dropout rate is 22.7%, according to the Ministry of Education [10]. The Technological University of Panama has a considerably high rate of early dropout (first or second year) in engineering careers across its various faculties [11]. This poses an alarming situation since school dropout not only affects the individual but also impacts society, the individual's community, schools, and the labor market, directly influencing the country's social and economic development.

Analyzing data provided by the National Institute of Statistics and Census (INEC) from the educational community of the Technological University of Panama during the period from 2016 to 2020 (last update) [12], concerning engineering careers across the six faculties of the university, we have structured Table I provides relevant information about university dropout rates in engineering programs within the six faculties of the university at the Victor Levi Sasso Campus. This table includes information about the faculties, the number of students enrolled in 2016, the number of graduates in 2020, and the corresponding dropout percentage.

It is essential to note that the presented dropout percentage does not solely refer to students who abandoned their studies but also includes those who still need to complete their academic programs. This approach aims to offer a broader perspective on attrition and the time required to complete the studies. However, we acknowledge that this interpretation may initially cause confusion.

It is essential to highlight some aspects regarding the analysis: i. the period considered is based on the curriculum of the engineering careers, typically five years, ii. The enrollment figures are exact for the year 2016 in the first year. However, due to the lack of granularity in the collected data, the graduation figures do not necessarily represent students enrolled in the year 2016; they may include students who enrolled before the analysis period.

TABLE I.
PERCENTAGE OF UNIVERSITY SCHOOL DROPOUT IN ENGINEERING CAREERS BY FACULTY OF THE TECHNOLOGICAL UNIVERSITY OF PANAMA CENTRAL CAMPUS IN THE PERIOD 2016-2020.

Faculty	Enrollment 2016	Graduates 2020	Dropout Percentage
Faculty of Civil Engineering	324	188	41.98%
Faculty of Electrical Engineering	263	145	44.87%
Faculty of Industrial Engineering	275	167	39.27%
Faculty of Mechanical Engineering	365	108	70.41%
Faculty of Computer Systems Engineering	421	74	82.42%
Faculty of Science and Technology	40	22	45.00%
Total	1688	704	58.29%

Source: [12]

Considering the overall result from Table I, it is concerning that during the period of 2016-2020, the percentage of students who possibly dropped out of the engineering program or have not yet completed their studies is higher than 50%. This represents a significant loss of human potential for the Technological University of Panama. Given these results, it becomes vital to identify the possible factors that could be causing this dropout for effective mitigation.

Having agile and versatile education systems is a result of knowledge advancements, technological innovation, and the volatility of the international economy [13].

According to a report by the Inter-American Development Bank [13], which aimed to diagnose higher education in Panama, several premises were put forward, highlighting the reasons why developing an intelligent university dropout prediction system conscious of the context using a microservices architecture is essential. These premises include:

Panama lacks sufficient reliable statistics and evidence to adequately analyze the outcomes of the current education system and assess possible reforms. There is an urgent need to develop more effective data collection systems that enable informed and evidence-based decision-making. Various institutes and training centers should provide comprehensive and regularly updated data to ensure efficient planning and management of the national education system, while also safeguarding data protection.

Adequate data and evidence are required for informed decision-making in Panama's education system. While there are compiled data by different agencies, they are incomplete and scattered, making it challenging to access and utilize them. A comprehensive and up-to-date database with extensive information, complemented by longitudinal studies, is needed to monitor, and evaluate the impact of the education system. Additionally, more transparency in delivering information is necessary to enhance the education system.

For each country, including Panama, to achieve exponential growth and keep pace with technological advancements, it is crucial to improve the traditional education system by adjusting objectives to new realities and inclining it towards innovation. This ensures that the human resources being formed can meet the changing needs of the labor market and society [14].

According to a report by the World Bank Group [15] following the pandemic, the loss of education could represent a significant income loss in the Latin American and Caribbean region, amounting to 1.7 trillion dollars. Moreover, the university dropout rate in the region may increase by 15%.

These factors underscore the importance of implementing an intelligent university dropout prediction system in Panama, one that is aware of the context and utilizes microservices architecture to address the challenges and uncertainties in the education system. By leveraging data, evidence, and innovative approaches, it aims to improve decision-making, adapt to changing realities, and mitigate the impact of dropout rates, ensuring the availability of skilled human resources for the evolving job market and society.

III. RELATED WORK

In recent years, information, and communication technologies (TIC) have gained great relevance in the educational field, where their use is observed through the implementation of distance learning (d-learning), followed by e-learning, mobile learning (m-learning), and the combination of the above in the well-known blended learning (b-learning) [16]. However, there is a new paradigm in computing known as ubiquitous learning (u-learning), which, through ubiquitous computing, allows the integration of various computer devices and communication technologies to facilitate the teaching-learning process and results analysis [7], [17].

The development of new tools to support education through ubiquitous learning technologies has led to the exploitation of microservices-based systems, which allow the integration of applications into small, completely independent, and decoupled programs that seek to perform a specific task within the development of a system [17], [18].

A. Context-Awareness in the Teaching-Learning Process

In the area of context-awareness for the teaching-learning process, Rabelo's systematic mapping [6] extensively describes context-aware ubiquitous learning environments, which have the capacity to collect, interpret, and utilize data and information from the student. These learning environments can change their behavior to adapt to students' learning needs [19]. Within u-learning environments, context can be classified as [20]: computational context (device, network, resources), user context (personal data, social situation), physical context (light, temperature, location), and temporal context (hour, date, year).

Continuing with ubiquitous learning environments, Wu [21] stands out with the proposal of situated learning in a ubiquitous context, meaning to use "authentic activities" from the real world to generate meaningful learning. At the same time, the system takes real-time student characteristics and provides them with greater personalized support.

A concept that stands out in the teaching-learning process and u-learning is personalized learning, for which Morrow [6] presents a context-aware ontology that aims to organize educational resources effectively, then filter them for a specific student with the application of computer resources, thus personalizing courses and study plans. This ontology is based on the PERCEPOLIS conceptual framework [22], which uses a hyponymy system and Pearson correlation [23], allowing the degradation of differences in terminologies and measuring similarity, respectively.

Specifically in m-learning, Yau [24] proposes a personalized and context-aware mobile learning (m-learning) application based on students' preferences in mobile learning. Initially, the study suggests that students' preferences can help understand learning styles, strategies, and characteristics, which, in turn, imply different levels of motivation, backgrounds, strengths and weaknesses, interests, and sense of responsibility, giving the necessary personalization to the application.

B. Microservices Technolohies in the Teaching-Learning Process

In the teaching context, Shulin [25] suggests an intelligent teaching system based on the microservices architecture, aiming to create a mixed integration environment that contains artificial intelligence, the internet of things, big data, cloud computing, and virtual reality, among others, efficiently guaranteeing system performance and scalability as needed. This integration is done to identify student characteristics, learning situations, automatically record students' learning processes, and evaluate results. In this way, it seeks to merge the physical and virtual worlds and gives students greater autonomy by efficiently recommending learning resources and convenient interactive tools.

Another well-known system is the Integrated Teaching System based on microservices presented by Peishun [26], which has among its main functions the analysis, management, and evaluation of student teaching. This integrated teaching system seeks to offer scattered teaching resources, online teaching systems, curricula, didactic resources, students, and teachers, to generate a much more efficient and unified service system, offering personalized teaching services to users and improving the results of the teaching-learning processes.

De la Cruz Vélez [27] provided important information about a microservices-based architecture to develop an academic control system. The system composition consists of a mobile application on the client side, while on the server side, non-functional components support the system's cohesion.

C. School Dropout Prediction Systems

In the study conducted by Mussida [28] at the Polytechnic University of Milan, an analytical learning tool was developed with the objectives of determining situations of students with a high risk of school dropout, providing support to these students, and implementing strategies to mitigate the factors that lead students to generate a high risk of dropout within the system. This tool presents a predictive analytical dashboard based on a multilevel linear regression model developed in R, which provides university staff and students with predictive information about students' status and the causes of possible school dropout. This tool encompasses static (personal data) and dynamic (exam grades) student information.

On the other hand, Cevallos et al. [29] proposed a model for predicting school dropout in university students of middle cycles based on economic, personal (lack of correct vocational orientation), and institutional factors. This model is based on three stages of the IBM SPSS Modeler methodology and uses cross-validation for validation. This study aimed to compare the effectiveness of two prediction techniques known as Bayesian networks and decision trees in the context of Educational Data Mining. As a result, Bayesian networks outperformed decision trees in all metrics stipulated in the model.

D. Methodology

For the development of this proposal, a qualitative methodology with a phenomenological approach [30] was used, as it allows analyzing and interpreting experiences from different perspectives regarding a specific topic. The initial phase deals with the process of searching, collecting, and analyzing information.

TABLE II.
ANALYSIS OF RELATED WORKS. SOURCE: SELF-MADE

Trabajos relacionados	C1 availability in the cloud	C2 context-awareness	C3 feasibility of using microservices	C4 orientation towards teaching	C5 predictive capabilities
Rabelo [7]	SI	SI	NO	SI	NO
Wu [21]	SI	SI	NO	SI	NO
Morrow [6]	NO	SI	NO	SI	SI
Yau [24]	SI	SI	NO	SI	NO
Shulin [25]	SI	NO	SI	SI	NO
Peishun [26]	SI	NO	SI	SI	NO
Zhao et al. [31]	SI	NO	SI	SI	NO
De la Cruz Vélez [27]	SI	NO	SI	SI	NO
Mussida [28]	NO	NO	NO	NO	SI
Cevallos et al. [29]	NO	NO	NO	NO	SI

Previously, several related research works have been described, which aim to pave the way for the proposal being made in this research. To do this, a comparison of the related works is conducted in Table II, considering the following criteria specific to the systems and their functions: (C1) availability in the cloud, (C2) context awareness, (C3) feasibility of using microservices, (C4) orientation towards teaching, and finally, (C5) predictive capabilities. These criteria are an adaptation of Pereira Da Silva's research [32] and are implemented to analyze specific technologies and functions of the previously described proposals.

The results of the compared criteria in Table II provide conclusive support for the described related studies, determining the importance of recognizing determining characteristics for the success of a microservices-based system, such as availability, flexibility, and long-term scalability.

IV. PROPOSAL

The present proposal offers a combined vision of the related studies, as the system intended to be designed, modeled, and developed is oriented towards intelligent context-aware prediction of school dropout. The main goal is to support and provide feedback to students about factors that could be affecting their performance within the educational institution. Simultaneously, the system aims to provide university administration with feedback on the student's situation to devise mitigating strategies for the most valued factors.

A. Design and Description of the PREMUCC Architecture

Due to its self-service nature, cloud computing can provide on-demand services while offering adequate network connectivity, a data resource environment, and flexible scalability [26].

In this work, the computational paradigm of the cloud is used, based on hybrid cloud architecture, to support the implementation of versatile, high-performance applications using the microservices pattern [33].

The architecture of the context-aware school dropout prediction system based on microservices, called PREMUCC, can be divided into four functional layers, as shown in Fig 1, described as follows:

- **User Layer:** The user layer is the presentation of the front-end application of the school dropout prediction system, including teachers, students, and administrative personnel, as well as PCs, mobile phones, tablets, and other multi-terminal application forms. The user layer provides input to the business process of the application system, enables psychological testing, and captures user data.
- **Processing Layer:** The microservices in this layer use the Representational State Transfer (REST) protocol to communicate with each other. Smartphones and tablets will enter through an API gateway, and computers will enter through user interfaces (UI).
- **Microservices Layer:** It contains microservices for end-users, such as students, teachers, and university administrative staff, with their respective profiles. Users can search, register, manage their profiles, add data, take psychological tests, and access school dropout prediction services. Although each database intercommunicates via HTTP request/response JSON, each microservice has a unique database that allows independent operation.
- **Data Layer:** It supports data communications, scalability, availability, and data integrity for the upper layers. It is a service-oriented data exchange and storage center that provides functions such as authentication, data capture, and analysis for microservices applications. It also supports data exchange and circulation between microservices applications.

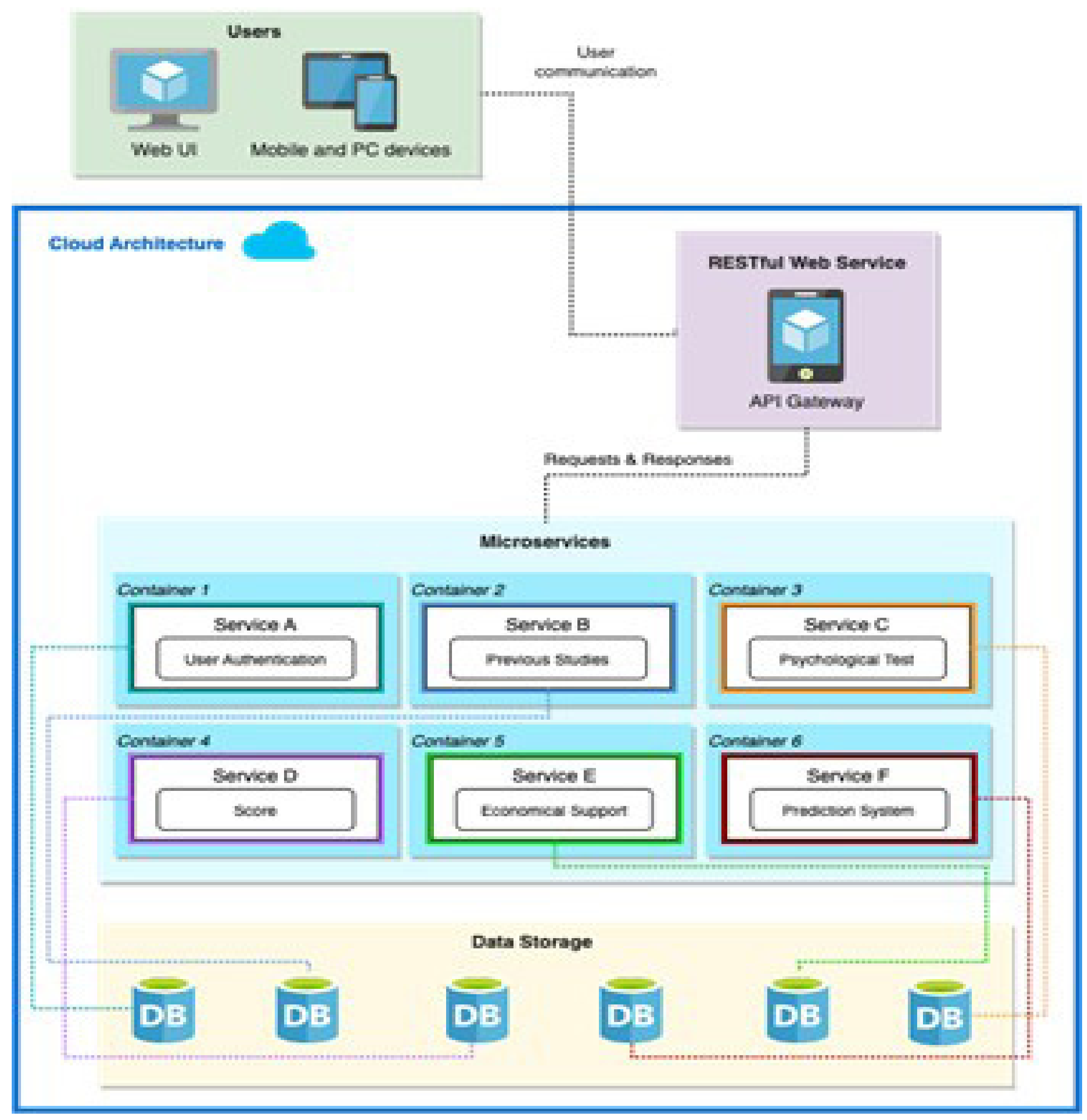

Fig 1. Architecture of the PREMUCC dropout prediction system. Source: self-made

Furthermore, the interactions of each microservice are independent of physical hosting, and these are handled individually or grouped in servers or containers [34]. Therefore, it is essential to consider the interaction model that will be implemented in the application, for example, for Remote Procedure Calls (RPC) and event-based interactions [35], whose purpose is to ensure that the architecture is robust against failures under continuous stress in different layers [36].

The microservices layer consists of six services, each residing within its container. Here are the functions performed by each of these services and their importance within the system:

- **Service A - User authentication:** This service verifies the user's identity when accessing the system. It checks if the user is registered and takes two necessary actions: prompting the user to register if not already done, authenticating the user's credentials, and determining their role in the PREMUCC system. The user's role dictates the actions they can perform within PREMUCC.
- **Service B - Previous studies:** This service is closely linked to the role of students within the system. It should be filled out when a student registers, aiming to verify variables related to the student's previous academic background, such as high school records, final grades, and subjects that might be potential weaknesses.
- **Service C - Psychological test:** This service allows students to take the university's psychological entrance exam and provides the test results.
- **Service D - Score:** This service stores the students' grades for the subjects they enrolled in each semester. It gets updated once the semester is completed. The main goal is to consider the student's academic strengths and weaknesses and create a historical record.
- **Service E - Economic Support:** This service aims to understand the student's financial status and the funding of their academic program. It also assesses whether the student has applied for financial support from the university, aiming to understand their financial context and whether it could be a determining factor in dropout risk.
- **Service F - Prediction System:** This service is the university dropout prediction system, previously trained with the variables captured by the other services. It activates once all the required fields are completed, providing a percentage to the student indicating their risk of dropping out. The student can request this information at any time.

B. Workflow and Operation of PREMUCC

Establishing the workflow and operation of the system is crucial as it defines the system's inputs and how information is stored, related, and provided to its users (see Fig 2).

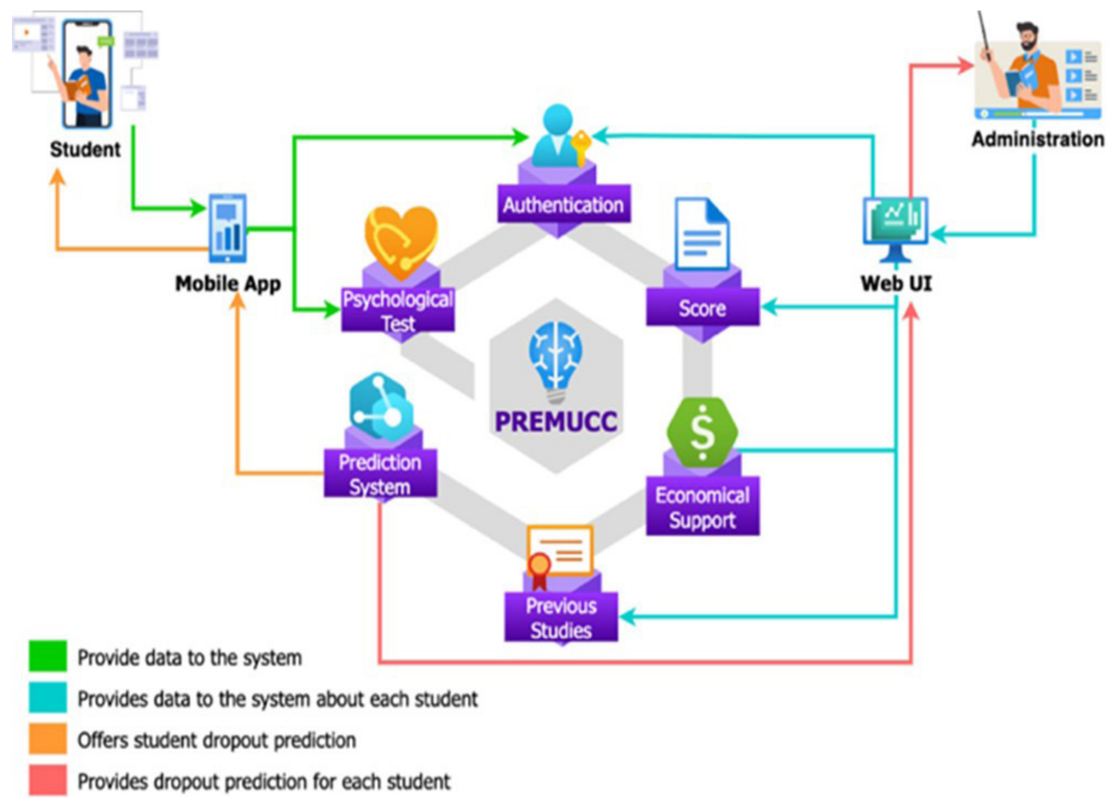

Fig 2. Workflow and Operation of PREMUCC. Source: self-made

The system involves two main types of users:

- **Students:** These are engineering students at the University of Technology of Panama who access the system via the mobile application and provide their data to the system. The main data inputs are taking the psychological test through the platform, and the results are stored in the Psychological Tests microservice. The system's dropout prediction model, housed in microservice F, presents the students' risk percentages of early dropout.
- **Administrators:** This category includes professors and administrative staff of the University of Technology of Panama. They are responsible for providing student-related data, such as their semester grades, previous high school grades, and information about any financial assistance tied to each student. The administrators can access a dashboard showing students at risk of dropping out.

All microservices provide information to both user types. Students can only see data linked to themselves, while administrators can access the entire repository. Administrators can create, update, view, and delete information within the system, whereas students can only upload and view data without the ability to delete it.

V. DISCUSSION

The architecture of the context-aware school dropout prediction system based on microservices aims to provide relevant information to the Technological University of Panama regarding the risk of early dropout among students in engineering majors. Previously in this work, a closely related study is a computational tool for predicting engineer dropout [22]. This project may have comparable points with the proposal developed in this work.

Firstly, the factors evaluated as inputs for the tool are crucial in determining the output and effectiveness of the model. Therefore, the input data includes personal information, demographic data, previous studies, finances, grades, and the student's major. The proposed system (PREMUCC) considers similar input data, but to recognize the student's context, it integrates additional information such as psychological tests conducted at the time of university admission, the shifts they attend, financial support (such as scholarships), and university entrance exams, which may influence the dropout scenario.

Mussida's proposed tool [22] applies Business Intelligence and the possibility of assessing an academic group, offering a monitoring panel of users' status. This centralizes the data, analyzes it, and presents it to administrators. In contrast, the present proposal is based on microservices that allow a decentralized system with higher performance rates and fault tolerance for systems that aim to scale over time. The prediction model is based on machine learning, using ETL (Extract, Transform, Load) tools to manipulate, transform, and classify the data for making predictions.

VI. CONCLUSIONS

The system proposed in this study aims to mitigate the high rate of early school dropout within universities by considering the context in which the student has developed before, during, and after admission to the major. It incorporates updated technologies that seek to address past failures, such as the architectural pattern based on microservices, context analysis of students, and the implementation of artificial intelligence for more personalized monitoring of the student's environment and performance. Mobile computing can benefit education by enabling students to access information and maintain their motivation. If a mobile application is used to access the proposed system, students can manage information instantly and in real-time, which may lead them to take preventive actions, such as taking reinforcement courses or applying for financial assistance offered by the university.

Regarding the analysis of related works that provide theoretical support to the proposal, there is a clear trend of developing tools that support the educational system in various areas with the implementation of new information and communication technologies (TIC), emphasizing the use of ubiquitous learning (u-learning) and microservices architectures. The objective is to deliver information to all students anywhere and to determine and analyze the context in which a person learns, with a high-performance system.

As a future work, developing and implementing the context-aware school dropout prediction system based on microservices (PREMUCC) is considered to evaluate its results and provide more robustness to the proposed architecture. It will be crucial to assess its effectiveness in terms of implementation and its impact on mitigating school dropout in the university stage.

CREDIT AUTHORSHIP CONTRIBUTION STATEMENT

L. Arenales-Gonzalez: Conceptualization, methodology, software, validation, formal analysis, research, data curation, writing - original draft, writing - review and editing, visualization, fund acquisition.

J. Gonzalez-Gomez: conceptualization, methodology, formal analysis, writing - review and editing.

J. Saldana-Barrios: Methodology, formal analysis, resources, Writing - Review and editing, Supervision, Project management.

ACKNOWLEDGEMENTS

Autor 1 y Autor 2. are supported by a scholarship from the National Postgraduate Strengthening Program of the National Secretariat for Science, Technology, and Innovation (SENACYT - Panama).

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