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Proposal of an Architecture for the Integration of a Chatbot with Artificial Intelligence in a Smart Campus for the Improvement of Learning

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Abstract: Traditional teaching based on masterclasses or techniques where the student develops a passive role has proven to be inefficient methods in the learning process. The use of technology in universities helps to generate active learning where the student's interest improves making him the main actor in his education. However, implementing an environment where active learning takes place requires a great deal of effort given the number of variables involved in this objective. To identify these variables, it is necessary to analyze the data generated by the students in search of patterns that allow them to be classified according to their needs. Once these needs are identified, it is possible to make decisions that contribute to the learning of each student; for this, the use of artificial intelligence is considered. These techniques emulate the processes of human thought using structures that contain knowledge and experience of human experts.

Keywords: activity recommendation; artificial intelligence; Chatbot; personalized education; smart campus

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1. Introduction

Currently, universities seek to improve their educational models by adapting to the needs of their students. One way to do this is with the use of information and communication technologies (ICT) by adopting them as allies to respond to these needs. ICTs improve processes and manage large amounts of information that can be used by universities and gain knowledge to improve management and educational models [1]. ICTs have changed the paradigms of society, even in the way we communicate this contributes to the continuous development of all sectors of the population. The penetration of ICT in society is so great that today we talk about a technological culture that has allowed the improvement of communication and with it, the spread of knowledge. Including ICT in all activities carried out by people allows improving the quality of life of people.

Educational environments, like all sectors of society, seek to evolve, improve the services and experience of its members. This implies that several of the university campuses gradually become intelligent campuses [2]. Smart campuses are conducive environments where ICT and campus members interact with each other to create an ecosystem where all campus resources are focused on meeting the needs of members. One of these needs and the most important for smart campuses is how to improve student learning in a sustainable way [3].

In order to focus their efforts on improving learning, intelligent campuses are based on a generic architecture focused on data management. The architecture of an intelligent campus takes, as main components, the new technologies or also known as emerging technologies. These technologies provide special features to the campuses included in a layered architecture that includes data acquisition with an internet-based approach to things (IoT), cloud computing processing. The data generated from the interaction of the members, as well as those of the administrative management, are analyzed for the obtaining of knowledge and decision-making that provides solutions to the needs of each of the intelligent campus members [4]. However, implementing these technologies has a certain degree of difficulty because when talking about improving learning, this means that smart campuses must provide a personalized education. Smart campuses have many benefits to provide personalized education, among these benefits are that students achieve a deeper understanding of the concepts of a particular subject. It promotes a positive attitude towards learning and consequently, a greater motivation towards the subject [5].

Smart campuses have strengthened their educational platforms and have improved their academic management capacity by being able to constantly monitor everything that happens in their vicinity. This is possible through systems of sensors and actuators, and computer applications that are responsible for identifying variables, making decisions and recommending activities to students. To meet these characteristics, the smart campus has complex architectures that allow it to manage a large volume of data in search of relevant information about its members. This process necessarily includes platforms for data management such as business intelligence (BI) or big data [6].

The use of each of these platforms depends on the volume of data generated by each institution, in addition to the characteristics of each one. Based on the results of the data analysis, it is possible to make effective decisions that contribute to student learning. An expert who, in the case of ICT, entrusts this work to the AI makes the decision. AI provides tools and techniques that allow us to face problems associated with decision-making. This paper proposes the development of a model that integrates variable identification and evaluation through the analysis of data that students generate in the academic systems that a smart campus manages. The results of the data analysis pass to an AI tool for decision-making.

This architecture has, at its disposal, the data of the students; these data can be structured and are generally stored in different database models. The architecture also manages the unstructured data that is obtained from the different IoT systems and that interact with the different members of the campus. The work proposed through the AI allows its interaction with students, becoming a permanent academic assistant that recommends activities to students. Each of the recommended activities meets the necessary requirements to be considered within a model based on learning. The activities are recommended within a learning management system (LMS). This condition requires the strengthening of the autonomy of the LMS with the objective that it works in its entirety in the AI system and can recommend the exact activities to defined groups of students [7].

The work is distributed in the following sections: Section 2 contains the theoretical basis that contributes to the design and complementation of the proposed model. Section 3 contains the method where all the development carried out is explained step by step. Section 4 presents the results found in the development of the proposal. Section 5 contains the discussion based on the results finally obtained and Section 6 presents the conclusions and future work.

2. Theoretical Foundation

In the development of this work, several concepts related to the smart campus architectures are used. It is important to know these concepts and be clear about the different pillars that make up the smart campus and how they will affect the proposed model. In addition, it is necessary to define the use of technologies such as AI, and as tools such as Chatbot which can interact with campus members and improve learning.

2.1. Smart Campus

To define an intelligent campus, it is necessary to start from broader terms such as intelligent environments. For an environment to be considered as intelligent, it must have the ability to solve problems. To do this, traditional environments such as a city welcome ICT and new technologies to solve typical problems such as mobility, security or personalization of services. This needs a robust architecture that supports data acquisition and analysis, cloud processing and decision-making [8].

University campuses are geographic locations as large as small cities. These campuses are composed of several faculties, libraries, green areas and other infrastructure, and house large numbers of people who are responsible for administrative or academic management. This concept makes the conception of a campus like that of a city [9]. They have characteristic features such as administration, ethnic diversity, and management models to meet the needs of their members.

A smart campus bases its operation on technologies such as IoT, cloud computing, data analysis and AI. Each of these technologies becomes a pillar of the smart campus designed to identify or meet the needs of its members. In addition, to meet the needs of members, the campus must do so in a sustainable environment with nature. To achieve this goal, each of the components enters into action and focuses on a specific task. The IoT, through systems of sensors and actuators interacts with the members of the campus without the need of a person or a computer [5]. The interaction takes place between the device and the person, the data is usually sent to the cloud computing and these are processed and emits a response or develops an action.

The analysis of data through an architecture such as big data can take the data that is generated from the members and when analyzed, it is possible to find outliers and classify them and find a solution through AI algorithms. A smart campus, in addition to the features presented, serves to include new technologies that can be replicated in larger environments such as cities [10].

2.2. Learning Development

Learning theories give clear guides on how students learn; this implies the relationship between the characteristics and instructional patterns that are usable when acquiring a learning strategy. Table 1 details the strategies recommended by the different learning theories in addition to the individual experience of the experts from the different areas [11]. Based on this knowledge, highly effective learning environments can be built. The table consists of each of the learning theories considered in this work, the characteristics used in each theory to associate them with different instructional patterns and generates or recommends a specific strategy.

Table 1. Relationship between student patterns and learning theories.

Learning Theory	Instruction Characteristics	Associated Instructional Patterns	Recommended Strategies
Conductivism Learn by imitation	Use experimental procedures Reactive Educating is passive	Tutorial Training Observation	Repetition Stimulus and response association Feedback Reading
Cognitivism Learn by association	Emphasis on reasoning Requires active participation to learn High level of cognitive processing	Simulation Updated information	Case resolution Rules essay Conceptual maps
Constructivism Learn by experience	Consider previous learning Flexible and modifiable knowledge Build knowledge actively	Research/construction exploration Scientific method Objective based scenario	Discussion panels Puzzle Design of collaboration experiences

With the clear concept of the theories on which learning is based, it is important to establish the actors involved in education in any educational model. This definition seeks to clearly establish the actors and their roles within education [12]. The student who is the owner of his learning and the teacher who guides the student on how to get to the learning. Considering that the student is the owner of his own learning, he relies on what he wants; for example, there are students who simply set their goal in passing a certain course and others in the real desire to generate knowledge about a certain subject. Here, the teacher goes into action because on him lies the task of proposing strategies that help him define what he wants the student to learn. Once defined what to learn, you have to look for techniques that help how to do it and that is defined within the learning processes. Finally, the conditions must be met for the student to learn. Under any learning scenario, the aspect that the teacher can vary to meet the objective of learning are the conditions, since modifying the conditions is modifying the tactics and modifying the learning and teaching scenarios. Next, their roles in learning are presented according to their participation guidelines.

Student Participation:

- They pass from a role of passive listening to active involvement in learning activities (readings, discussions, reflections, etc.).
- They engage in higher order thinking processes such as analysis, synthesis and evaluation.
- They learn in dialogue and in the interaction with content and skills development.
- Students receive immediate feedback from the teacher and their classmates.

Teacher participation:

- Design the activities according to their discipline and the curricular moment that their students live.
- They adapt the learning activity to the possibilities and needs of the group.
- They facilitate the process of the activity taking care of the extension and depth of the knowledge that is addressed.
- Feedback in a timely manner on the performance of the group and the students individually.
- They are oriented to the development of students' competencies according to the discipline and level of the course.

2.3. Chatbot as an Artificial Intelligence Tool

Chatbots or conversational assistants are computer programs that are capable of interacting with the user using language-based interfaces. The main objective of a Chatbot is to simulate an intelligent human conversation so that the interlocutor has an experience as closely as possible to the conversation with another person.

Among the actions that a Chatbot offers the user is to provide information about a product, event or carry out an action. The general functioning of Chatbots starts with the use of natural language [13]. However, it is also based on defined flow conversations, based on structured interactions that generate few ambiguities of meaning.

An alternative is conversational bots based on decision trees or driven by artificial intelligence. The interface used by Chatbots is based on the structure of human conversation that is obtained through natural language processing (PLN). The PLN allows algorithms to understand, interpret and manipulate human language [13]. In addition, more advanced Chatbots are able to learn from conversations by implementing Machine or Deep Learning [14].

Chatbots, to be able to carry on a conversation with the user, must have the following components:

- Conversational artificial intelligence is the engine of Chatbots. Through this tool, it is possible that the management and processing of natural language is carried out. Through conversational AI, Chatbots have the ability to analyze user entries, learn from them and generate a response as appropriate as possible in relation to the input entered.

- User experience (UX), is responsible for making the conversation between the Chatbot and the user as natural as possible and that it is intelligent and logical.
- User interface (UI), is the component through which the user interacts with the Chatbot, that is, they are the elements that the user can physically see and hear to make decisions and follow the conversation.
- Conversational design is a design language, which is based on human conversations. It is the conversational design and responsible for providing human logic to an artificial intelligence.

To obtain a coherent conversation between the Chatbot and the user, it is necessary to establish a good algorithm design; that is to say, that both conversational AI, UX, UI and the conversational design must be correctly related to each other and well defined. Additionally, the algorithm when being implemented with AI must be trained to be able to interpret user input within the conversation, understand the questions and decide what to answer. This capability is possible thanks to the processing, comprehension and natural language generation technologies such as AI. There are two types of Chatbot according to complexity, a first type of structured or first generation Chatbot, which bases its operation on a set of rules. A second type of generative or second generation Chatbot that uses machine learning, artificial intelligence or other machine learning mechanisms to interact with the user.

The need to share information and resolve doubts make Chatbot tools very useful in educational environments. The incorporation of Chatbots in education must be preceded by a prior reflection to define what its purpose in education is. For this, an institutional and organizational debate is necessary to guarantee functionality, viability and scalability within the institution [15]. It is important to note that the inclusion of Chatbots does not replace the teaching figures or those of administration and services staff, but instead replaces some of the tasks assumed by these figures, complements and helps them.

Thanks to the UI based on conversation, Chatbots have become present in student interactions with information and content. This ability places them as mediators of these interactions in online learning environments. Chatbots base their UI on menus and buttons that, allow the person-machine relationship from search keywords. Everything a student or teacher needs can be requested through an easy consultation using natural language. Thanks to this, the Chatbot can be configured as a new UI/UX by enabling, facilitating and expediting access to information.

For example, when consulting the Chatbot, students can access information that is difficult to locate within an LMS environment. For students, it is useful to resolve doubts quickly at all times and immediately. For teachers and learning managers, this tool allows to track the evolution of your students or use it as a resource for learning support [16]. One of the advantages of Chatbots is that they do not occupy too many computing resources, user experiences become more enjoyable, and interaction increases interest in the subjects.

The presence of Chatbots will also depend on the number and type of interactions they can make with other Chatbots or tools. In this way, functionalities are incorporated where data converges that allow executing integrated actions. An example is the Chatbots ability to collect personal email information, combine it with the calendar and information available on the university's website to reconcile the data and confirm a tutoring with a teacher.

3. Method

To improve learning through the personalization of education, it is important to establish an AI model that suits the infrastructure of the smart campus. The architecture of the smart campus is composed of layers and it is important to establish what is the incidence of each of these in the operation of the AI [17]. The layers of the campus architecture are shown in Figure 1. The first layer is responsible for the acquisition of data that gives priority to the use of IoT devices. Several of these devices interact directly with the members of the campus that have been divided into three groups to segment what each one does. In the first group are those in charge of all the administrative management of the campus, the second group is made up of teachers and the third group and the one with the greatest emphasis on this work is that of students. The IoT devices adapt to the needs of each group and obtain important information about each of the activities they carry out. In the specific case of the students, the different IoT devices as well as sensor systems acquire information from the students, such as the effective time that each student spends in the university, the places he frequents, as well as acquires information about the activities he performs and his qualifications. This information is important at the moment that the AI has to draw a conclusion about some event that it is analyzing.

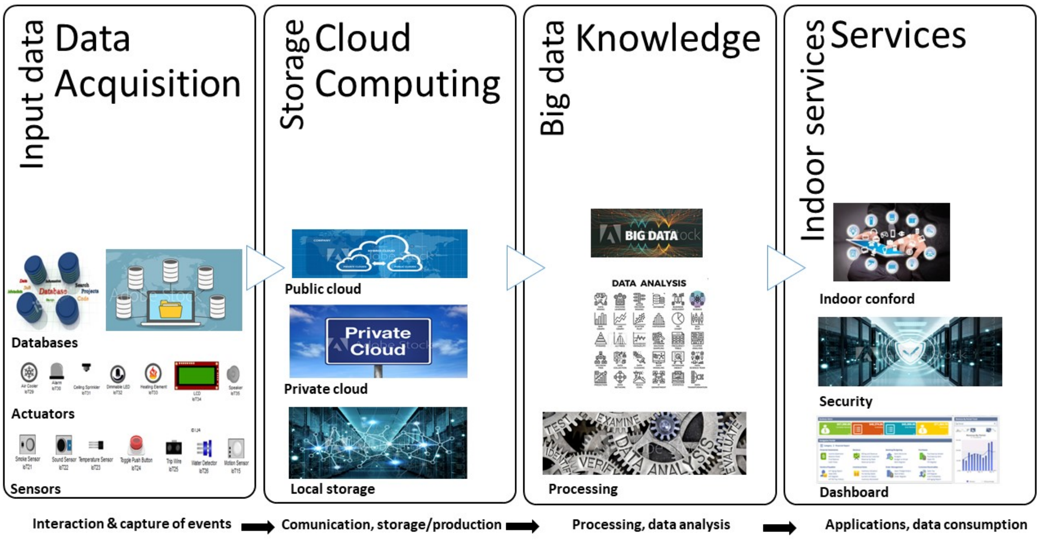

Figure 1. Layers of the architecture of a smart campus and its impact on the components of a Chatbot that uses artificial intelligence [18].

In the second layer is the computing process which usually makes use of public or private clouds. In this layer, the architecture of the smart campus is responsible for storing the data in several sources that can be databases or sends the data to the cloud to perform some type of processing, such as, for example, in the area of security access to Restricted areas which are through facial recognition, so AI algorithms use clouds such as Microsoft Azure or Amazon.

The third layer is data analysis. To carry out this process, a Hadoop is used as a big data framework. This layer is one of the most important because it is responsible for the analysis of all data, whether structured or unstructured, that are in the cloud or in a local storage. This data is processed by Hadoop and presents the information to the integrated AI to a Chatbot. The Chatbot continually consumes quality information offered by the analysis layer and can reach conclusions or learning in a deeper and faster way. The Chatbot knows all the information of each of the students through Hadoop, as this information is of quality and guarantees that the data is real and verified on the tendencies of the students, as well as the progress that the students present in each subject. In this way, the Chatbot integrates the analysis data carried out in this layer into its analysis and also has the information obtained directly from its interaction with the user.

The knowledge layer is responsible for exploiting all knowledge and displays it through dashboards or control panels, as well as applications that are used by students. The student consumes the Chatbot data through the use of the campus LMS which is the application where the system is embedded, and every time a student accesses the LMS it starts the Chatbot module with the user identification and it begins to interact with the use of several questions in natural language.

For its application, it is necessary to establish a system that is most relevant for students. The smart campus has several systems that are at the service of students. However, these systems work on an intranet and this is a disadvantage for use if the Chatbot is applied or integrated into one of these systems [19]. The access and services of this tool would be available only to people who are inside the campus. The objective of this work is that all students benefit from the Chatbot on- or off-campus. One option is to apply it to the website of the university, however, what is its benefit and what users would be considered?

The university's website is accessed by people who generally seek information on the careers offered [20], as well as news related to the events that take place on the university campus and which promote their position and competence [21]. The indicated thing is to implement the Chatbot in an academic platform that is used continuously by the students and that keeps clear information about the students' performance. It is for this reason that the most appropriate option focused on the use of LMS. Smart campuses generally have powerful LMS where students have available resources and perform their activities. The LMS, in addition to simple repositories, have become true assistants for both the teacher and the students. Figure 2 shows the architecture that the AI-based recommendation system obeys [22]. This architecture has four stages that are integrated into the smart campus where each stage is related and must be met to obtain adequate results and value for learning.

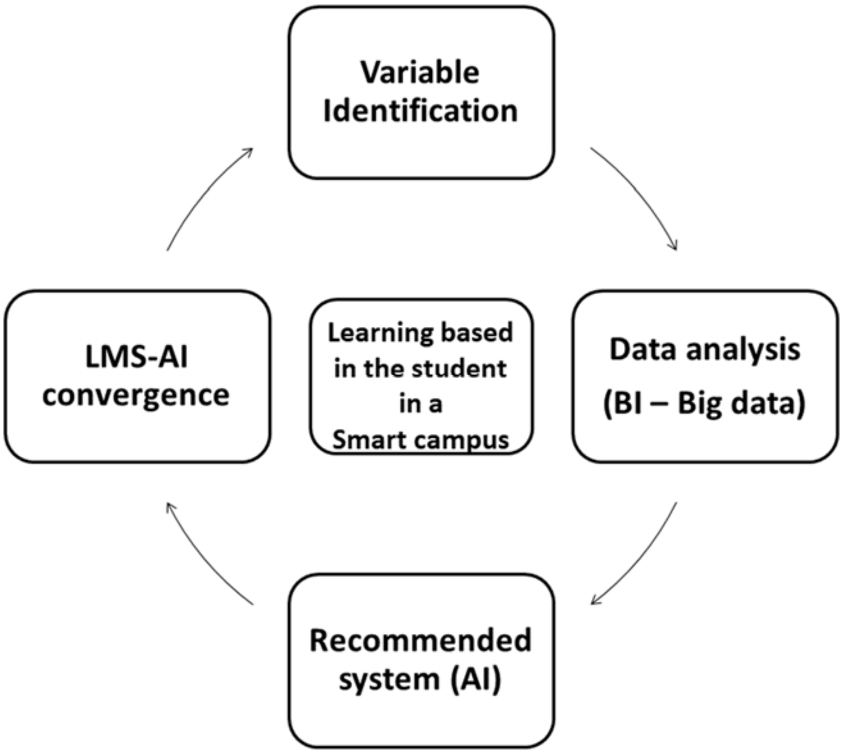

Figure 2. The architecture of a comprehensive system for the development of a learning environment through the recommendation of activities.

3.1. *Variable Identification*

In the identification of variables, all the tools and systems that the smart campus has to acquire information come into play. In a traditional campus, a student's performance can be measured based on their academic records, which is usually not necessarily enough. On the other hand, a smart campus has the possibility of increasing the number of variables that affect the academic performance of students [23]. For example, in a smart campus, the IoT allows identifying very interesting aspects and trends of each member.

One of the aspects that can be identified is the time a student stays on campus. It is even possible to identify the time the student spends in class since the time a student spends on campus does not necessarily imply that he is receiving classes. Identifying these variables is possible thanks to facial recognition systems or tag readings of each student's identifications [24]. Another variable that is possible to identify, is the attention in class that the students show, as the IoT allows through sensors and cameras to detect the fatigue and the attention that the students give to each one of the classes.

Detecting these variables results in the conditioning of the environments, as well as the improvement in the educational models of the campus [25].

In addition to IoT, there are also traditional computer systems that store information in transactional databases. Likewise, there is the LMS, which serves as a repository and main assistant in the development of activities and review of resources. The LMS is also very helpful in identifying variables related to the autonomous work that each student performs [26]. Even more, the LMS allows measuring the performance of students in an online mode if the smart campus offerings so arranged.

The greater the number of variables included in the analysis, the greater it is possible to identify with greater granularity the problems that each student presents [21]. Accordingly, the AI model will be more effective when recommending the activities that align to each student. Another way to identify the variables related to academic performance is the AI model through the implemented Chatbot. Unlike other AI models, the Chatbot is constantly interacting with students and obtaining information from them. Therefore, the development of, in addition to recommending activities, seeks to learn from each student by identifying their needs directly [27].

The AI model identifies the academic, psychosocial and environmental variables that influence students' academic performance. Figure 3 identifies each of the variables that are considered for data extraction from data repositories that a university has. In academic variables, student performance and integration are considered. Psychosocial variables include objectives, alignment, peer interaction and interaction with teachers and the LMS [17]. Environmental variables are parameterized according to financing, external social relations, transfer opportunities and interaction with teachers.

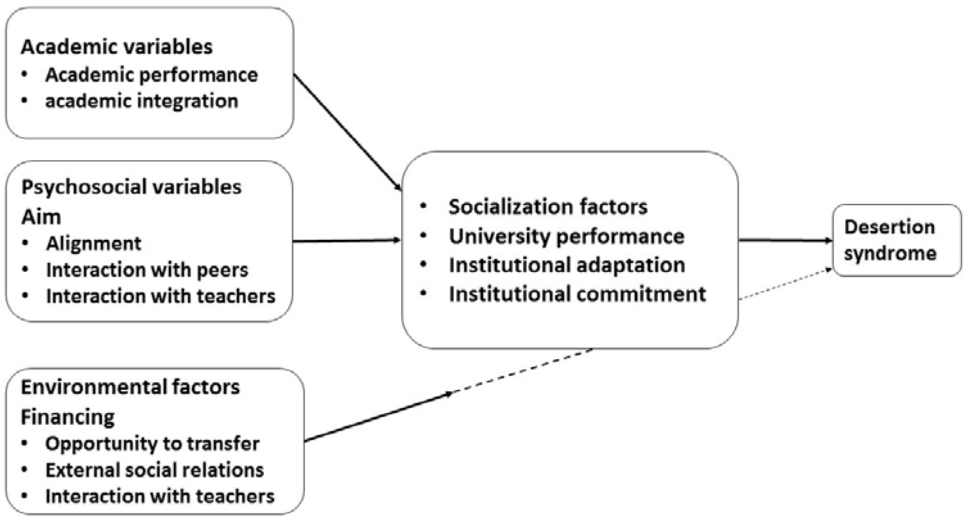

Figure 3. Model for the identification of variables that influence academic performance in a smart campus.

3.2. Chatbot Integrated Architecture - Smart Campus

The integration of a Chatbot to the architecture of a smart campus allows decision-making automatically, and also provides support and monitoring of student activities. For this, it is necessary to define how the AI adapts to an architecture that handles other technologies and that allows the management of large volumes of data. Figure 4 shows the diagram that responds to the smart campus architecture and how it links to the phases of a Chatbot that uses AI. The conditions under which this integration is developed is in an intelligent environment that manages an architecture based on data management. To do so, it has a big data framework that has already been mentioned. Each of the Chatbot components adapts and uses the infrastructure already deployed on the smart campus [13].

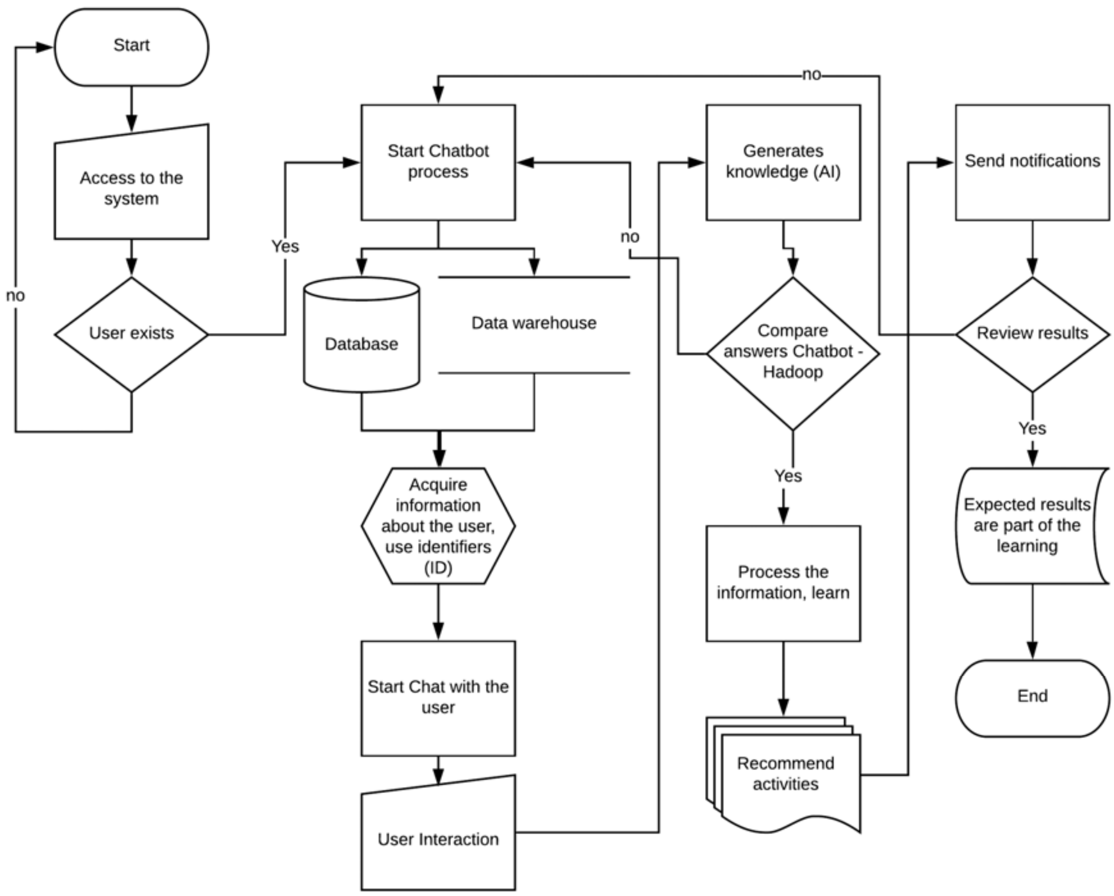

Figure 4. Operation diagram of the integration of a Chatbot in a smart campus.

The Chatbot is a module that needs to be available for interaction with each student, so it is linked to the LMS used by the university. This integration seeks that first the AI module integrated in the Chatbot has direct access to the information of each user accessing the LMS. This guarantees that during the interaction process, the Chatbot establishes that the user is who they say they are and that they also have a history of the student with their qualifications, as well as preferences previously discovered by the smart campus. With this definition of the environment, it is possible to understand what each of its components does and how it interacts with the user and the environment.

The process begins when a user accesses the LMS of the smart campus, the LMS stores information on the qualifications of each of the students, as well as important records on their performance in each of the activities. The use of the LMS is mandatory by the guidelines and policies established on the campus where this work was carried out, and this guarantees the availability and access to information. Once the user accesses with their credentials, the first security parameter is carried out if the access validation is correct, and it goes on to the next phase, otherwise it returns to the beginning and again requests its credentials. If the access is correct, it automatically starts the Chatbots work, who interacts with the student with a welcome dialogue and verifies what are the pending activities or tasks that he has. This first analysis is done directly in the LMS, which is where the task log is located. The Chatbot immediately notifies the student of the pending activities and the achievements obtained in which they have already been carried out. This is done by the AI module with a review of the report card and also processes the information that has been analyzed by Hadoop and that is in the data stores, and the data analysis layer provides information on other systems that provide with the time the student spends in the university or the time dedicated to the development of activities in the LMS [28]. This information is in different repositories and the search is done through a user identifier to ensure that there is no data exposed in the process.

Once the Chatbot knows this information, it interacts directly with the user, establishing questions and answers about the student's academic performance. AI allows the interaction to take place in a natural language and the answers it obtains compares them with the information it knows. This process is a way in which AI systems can detect the truthfulness of responses and improve their learning. The Chatbot processes the information available to each student considering the results obtained Hadoop and the conclusions reached by the interaction with the user. This allows you to know what the qualities of each student are and what activity suits their characteristics and needs. If the Hadoop data and those obtained from the interaction with the user do not correspond, the AI module returns to the beginning of the process in search of more information in the data repositories and asks the user new questions to adjust the weights and reach a satisfactory conclusion.

With the result of the analysis, the Chatbot recommends the activity that has the greatest weight and notifies both the teacher and the student and starts an evaluation stage. In this stage, he compares the qualification obtained and whose result responds to the management of a rubric to the activity history. If the achievements are adequate in each criterion of the rubric that has been previously reviewed by the academic areas in charge, the results are stored and taken as success stories for cases that are marked by similar patterns and the process ends. If the results are not adequate, the Chatbot starts the process again in search of more detailed information, adjusts the weights and feeds the system until the criteria of the rubric are met.

The information management adheres to the internal guidelines of the smart campus, as well as the policies and law of Ecuador, this being the country to which the university where the work has been carried out belongs. As referential measures, the entire process and management is already established and executed within the architecture of the smart campus that manages all the information. However, reference can be made to the fact that data is processed through policies and processes generated by the Ethics Department of the smart campus. For this context, the data does not contain information of the person, and the identifier that is used is proper for the analysis, this hides the user. In the interaction with the user, the Chatbot is forced to carry a personalized service for which it uses the first name of each person. These names are stored in temporary variables that delete user information at the end of the session.

When there is a need to carry out an analysis of information that involves the personal data of the members of the campus, a process is carried out in which the relevant authorization of different areas is requested, as well as that of those involved. The ICT departments have processes already defined and aligned to the reality of each university. For this reason, these should be considered when adjusting the data management architecture and then that of AI.

3.3. Analysis of Data

Data analysis is important in this work because it is the one that identifies the students' progress in learning. To meet this objective, it is necessary to include a tool capable of extracting data from any type of source, transform them and upload them to the next phase of the AI model for the personalization of education. There are several tools with these capabilities, including several of these specializing in fields such as health, marketing, geolocation, etc. There are two favorable platforms for data analysis. The first is the use of a BI applied to the analysis of academic data and a second option is the use of a big data architecture [29].

When contextualizing the data analysis options, there are several differences between them. The advantage of implementing a BI that focuses on academic data analysis is that it is a technology widely deployed in the industry and its results are well proven [30]. The implementation, although it has its degree of complexity, is easy to overcome due to the amount of existing information. The technology they use can be with a commercial or open type license and technical support is available in both cases. As for disadvantages, a BI has limitations in large volumes of data which results in penalties in processing [31].

Another solution is the use of a big data architecture, which handles large volumes of data very well and presents incomparable improvements in the processing part. To this advantage is added the ability to analyze the data regardless of the format in which they are. Big data is considered as an emerging technology that, due to its analysis capabilities, is applied in large environments or in processes that generate a large volume of data [32]. These characteristics are diminished by the complexity of its implementation and by the high requirement of knowledge that the people in charge of the implementation must possess.

This work focuses on the use of big data architecture for data analysis and management since it is a problem already developed by the authors. This allows us to focus on the design and functionality of the artificial intelligence model, knowing that the data analysis process has been sufficiently tested in a smart campus [33].

3.4. Model of a Chatbot with the Use of Artificial Intelligence

The AI model for recommending activities should be adjusted to the needs established to improve learning [21]. The most common models of AI are expert systems, recognition systems, behavior-based intelligence, etc. Ideally, it should focus on a type of model that fits the needs of the students and whose interaction contributes to the motivation of the students [27]. One of the tools that most enhances the handling and interaction with users is the Chatbot. The Chatbot is comprised of computer programs with which it is possible to have a conversation [34]. This ability allows to request some type of information or to carry out an action. The Chatbots incorporate artificial intelligence systems. Therefore, they have the possibility to learn about user preferences over time. In general, the use of Chatbots is focused on marketing tasks or disseminating information about a product [35].

However, aligning and modifying a Chatbot to improve the learning process of the students of a university depends on several parameters such as knowledge of the variables and the infrastructure where they are applied. Figure 5 contains the architecture of this model coupled with the results obtained by the analysis of student data [36]. The phases of the architecture start from the user interaction with the system, and this interaction uses a channel that, in this case, is done through a chat or SMS.

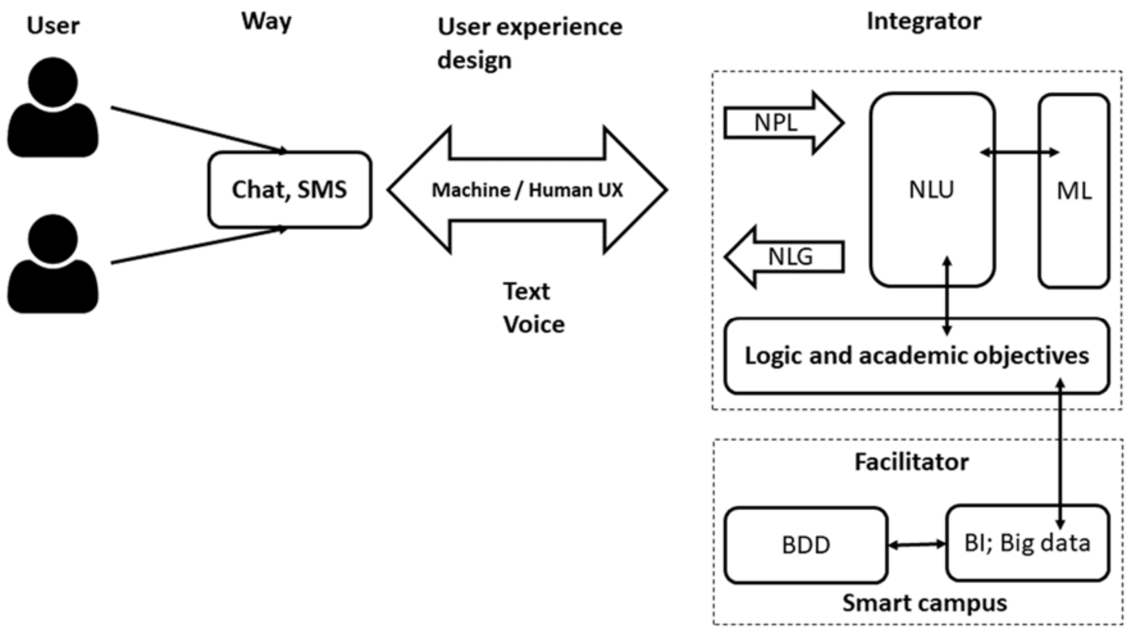

Figure 5. Communication architecture between a Chatbot - Smart campus.

The objective of implementing a model integrated into a smart campus is to help improve student learning. For this, it is necessary to know the architecture of the smart campus and the methodologies that teachers use within the classroom [2]. These methodologies are reflected through different activities and evaluation mechanisms developed by the students. The activities and resources that each student has for the development of a subject are in the LMS. The centralized management of activities makes the LMS the main system that the student uses for most of his academic activities. This specification is important because LMS integrates the Chatbot that interacts directly with the student. For example, a student at the beginning of the session in the LMS also starts the Chatbot, in turn, this system automatically knows who it is and has at its disposal all the information that has been treated in the data analysis. Therefore, the Chatbot knows in advance what are the strengths and weaknesses of the student who has entered the system.

The Chatbot uses the communication channel with the user and continues towards an intermediate layer known as user experience (UX). These systems handle two types of UXs, the UX Interface and UX Writing. The first one is dedicated to defining how content is displayed within the channel and is usually built by the channel, for example, Facebook Messenger [37]. The second UX refers to how the bot communicates with the user through texts, images, videos, conversational flows, contexts and the whole series of tools that allow answering everything the user asks or answers.

The next module is the integrator. This is the key piece of a Chatbot, delivers all the natural language processing (NLP) tools, and is the AI part of the Chatbot. The NPL is responsible for the process performed by the machine to acquire, identify and process natural language, once processed it is passed to another process known as natural language understanding (NLU). The NLU identifies the user's intention. What does the user want? The NLU is a process that goes hand in hand with Machine Learning (ML). The Chatbot integrates pre-established rules of AI because below this, it integrates a neural network that allows this to learn, and this implies that the Chatbot needs to be trained to suggest the activities that meet the needs of the students.

In the module of the facilitator are all the data that have been previously worked by both data analysis or external systems and additional databases for student identification. In the facilitator, the academic part communicates with the logic of the system for this case. For example, the student who started his session at the LMS has a record of activities that need your attention, and this is where Chatbot comes into play [38]. This begins with a greeting and automatically communicates to the student all that is pending, in a second phase the Chatbot has the information about the activities in which the student's performance has been low. These data come from the data analysis and are found in the facilitator. With this information, the Chatbot starts a second interaction with the student. The objective will be to look for the reasons why it has failed to develop these activities. Both the NLP and the NLU come into operation and interpret the student's situation. By integrating module, it concludes what the student's needs are and recommends a specific type of activity from a catalog that is stored in the LMS learning module.

Figure 6 explains the operation of the Chatbot and each of its phases by means of a flow chart. The student, when accessing the LMS, launches the Chatbot application and begins the interaction with an initial greeting. The Chatbot processes and analyzes the information generated from the interaction, in addition, the data obtained from the big data framework is added to the analysis. Once this analysis is done, the AI module verifies the fulfillment of the different activities assigned to the student. The analysis is done in two stages. The first is responsible for reviewing the compliance of the activity. The second stage analyzes the student's academic performance in relation to the activity. It should be emphasized that each qualification of the activities responds to rubrics that constantly evaluate the scope of the learning evaluation criteria. If the activity has been fulfilled and reaches the learning percentages assigned to the activity, the AI module reviews the pending activities that the student must perform, as well as the due dates. Once you have this information, notifications are scheduled on the student's calendar and the Chatbot notifies the student in natural language of everything that is pending and ends the session.

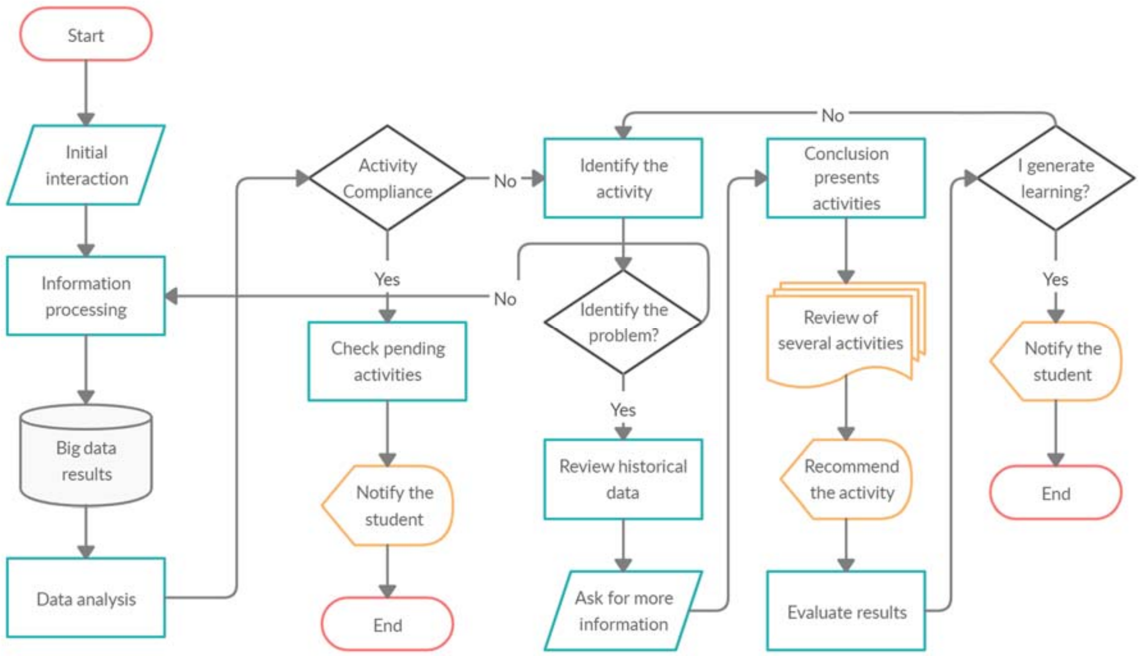

Figure 6. Chatbot behavior for the recommendation of activities.

If there is an activity that has not been fulfilled or the student did not reach the minimum percentage in the evaluation criteria for the generation of knowledge, the Chatbot begins a process to identify the exact activities in which the student presents a low performance and which are the causes. If the problem is identified, the AI module reviews the student's history through the use of the data it manages and engages in a new interaction with the student. With this new interaction, the Chatbot seeks to clarify what are the problems that cause the student's poor academic performance. This process is done through questions on the subject and offers several alternatives to the student that is based on the recommendation of activities. The Chatbot comes to a conclusion with this new information and reviews in its catalog all the activities that align to the needs and patterns detected in the students. This pattern analysis is a phase developed in the architecture of the smart campus through Hadoop. With this information, the Chatbot recommends the activity to the student and once it has been developed and qualified, the AI module enters the evaluation phase of results. The objective of this phase is to establish whether the development of this activity aligns with the needs of the student. If the evaluation has satisfactory results and the student's learning is verified, the Chatbot generates knowledge about the case, notifies the student and ends the process. If the Chatbot detects that the desired learning was not achieved, the process returns to the identification of the activities and the process is repeated, discarding the first activity and recommending the next.

4. Results

Implementing a Chatbot, as proposed in this work, allows establishing an appropriate pedagogical model where students address different topics and reflect among themselves based on the establishment of starting questions asked by the Chatbot. In addition, it allows capturing the conversation with users to perform a cognitive and affective analysis or exploration of students' perceptions of a specific topic, interaction, situation or context. When analyzing the results of the implementation of a Chatbot in the LMS of the university that participates in this research, the students presented a considerable improvement in their academic performance in the following aspects.

4.1. Participation in Classes

To perform Chatbot adjustments and tests, this was implemented in two courses consisting of 24 students each. According to the reports presented by the tutors of these courses, 59% of the students showed greater interest in the development of the activities in a period of 30 days, this measure was made with the report of activities carried out available in the LMS. Students, through Chatbot, have access to academic information, such as notifications about upcoming assignments, grades and deadlines for all activities. For students, the use of Chatbot allows them to have an academic assistant who can only interact with him. In addition, Table 2 shows the problems detected through the interaction of the Chatbot with the students and that are taken as a cause of the lack of interest of the students in the development of activities [39]. For this exercise, five common problems have been identified within the education model managed by the smart campus. The data were obtained through the interaction with the Chatbot asking questions in the form of surveys conducted to each student course. For this, the students have been divided into groups 1 and 2. This assignment is used to effectively manage the results, and the degrees of involvement of the problems in each group are evaluated by means of the high, medium and low criteria.

Table 2. Problems identified in a traditional teaching model through the use of a Chatbot.

Problems Identified	Group 1, Number of Students 24	Group 2, Number of Students 24
Absence of significant interactivity	Low	High
Continuous text reading activities	High	Half
Lack of assessments and exercises	Low	High
The absence of the feedback mechanism	Low	Low
Insufficient or unclear instructions for use	High	Low

The results of this survey are described as follows. For group 1, the problems, activities of continuous text reading, instructions for insufficient or unclear use are considered relevant. For group 2, the problems with the highest incidence are the absence of significant interactivity and the lack of evaluations and exercises. With this information, it is possible to improve the educational model embodied in the LMS, and this is possible through the creation of better activities, as well as the updating of the resources available to students.

4.2. Monitoring in the Development of Academic Activities

The data of the samples analyzed in the first 90 days after the Chatbot implementation shows a relevant change in student performance. Table 3 shows the activity compliance data in relation to the tasks sent, completed, delivered and the depth of development versus the corresponding time period. The period of time considered is 90 days from the implementation, however, in the second column the percentage of production without the Chatbot implementation is placed as a reference.

Table 3. Student productivity in the LMS with and without the use of Chatbot.

Activities and Tasks	Without AI Application	First Sampling Period (30 Days)	Second Sampling Period (60 Days)	Third Sampling Period (90 Days)
Tasks Sent	25%	25%	28%	32%
Tasks Completed	80%	84%	88%	93%
Tasks delivered	82%	86%	92%	96%
Development depth	61%	64%	77%	83%

In all cases that arise in relation to the tasks performed by the students, there is an increase in the academic evolution of the students. This is a result of the AI implemented in the LMS. The AI, upon knowing in advance the academic performance of each student and what are the activities that each one must perform, sends notifications until the student completes the tasks. In the depth of the development field, the quality of the work sent by the student has been measured. Unfortunately, it is not yet possible to evaluate this parameter for the system. To solve this deficiency, the AI system becomes an assistant for the teacher of the subjects and notifies what are the pending activities. This is complemented by the system configuration so that the evaluation of all activities is carried out by means of rubrics. This solves the problem of AI because, by having percentages in each criterion of the evaluation rubrics, the system can deal with this information and process it to perform the analysis.

4.3. Activity Recommendation

For the recommendation of activities, the AI system is based on a process of analysis of all the data that it has at its disposal and that is stored in the LMS. The LMS data may not be sufficient when recommending an activity that aligns with a student's skills. For this, the AI uses the Chatbot as a means of interaction with the student, and that collects direct information from the student to add it to the analysis [3]. In Figure 7, the stages that make up the recommendation of activities are observed, each of the stages depends on the previous one and everything works in relation to the analysis of student data. For the analysis, the data comes from several sources; in this work, the LMS, academic and financial databases and external information that can be collected by several systems or people who are responsible for the academic follow-up have been considered as main sources.

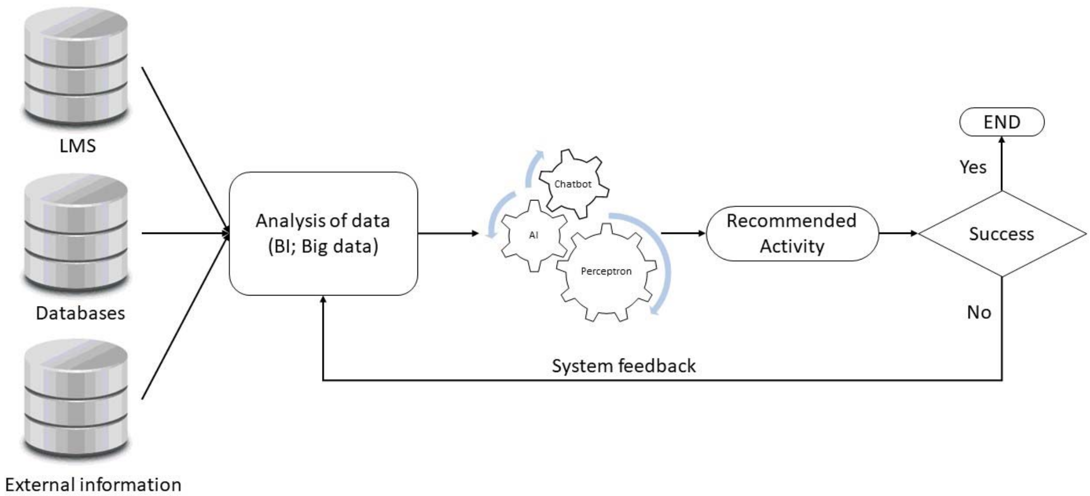

Figure 7. Stages for the recommendation of activities using a Chatbot that integrates artificial intelligence.

In the next stage is the data analysis, this being the main component used to know what happens to the students' academic performance. In the Figure, the possibility is left open to the use of a BI or big data architecture, and the reason for this is because the recommendation system is generic and can be coupled to the two technologies [40]. Data analysis seeks to establish what are the variables that cause poor academic performance in students. Upon discovering these variables, the exact causes of the problems are established, such as dropping out of school or low graduation rates in different careers [41]. The way in which these variables are evaluated is by subjecting the data to debugging and filtering processes that allow reliable data to be handled for analysis. These models are generally applied through data mining algorithms [29].

Data mining algorithms look for anomalous variables and have the ability to group them by facilitating decision-making on these results. Preprocessed data along with the use of data mining algorithms can identify patterns in students, for example, it is possible to detect students who have poor academic performance when developing questionnaire-type activities. This example, although it is very simple and does not talk about the great potential of data mining, shows what can be done at this stage. In addition, it is possible to combine the algorithms to improve the evaluation of the results and provide greater granularity to the system [42]. The common thing in an analysis is to use cluster algorithms to be able to treat the information that is presented similarly in several students. If we return to the previous example, it is possible to obtain several groups where students with similar characteristics are identified in the development of the proposed activities or tasks [43]. In this way, it is possible to propose several tasks that adapt to the clusters, improving management in decision- making.

With the knowledge provided by the analysis of student data, the next stage is part of the AI. To achieve this, the Chatbot manages a model based on neural networks, which allows it to learn from users. To simplify the process, the Chatbot has the data of the students which allows it to relate this information with that obtained from its interaction and complements it to make better conclusions.

The recommendation of activities is done by the Chatbot directly and through natural language with the student. The recommendation is made directly at the time the student enters the LMS. This recommendation is made based on the data about the student's performance in each subject he takes. In the same way, this recommendation can be made through notifications that are integrated into the LMS interface or can even do it through emails or messages to the student's devices.

Another way of recommending the activities is based on the knowledge obtained from the interaction with the student; for this, the AI module asks several questions where it first determines that the user is who he says he is. Once the identity of the user is determined, the Chatbot goes to a second stage where its objective is to identify the strengths and needs of the student and learn from their responses. The two ways to recommend activities converge for a better understanding of the activities that best fit students.

In the last stage, the system verifies if the student has improved; this verification will depend on the qualifications received from the activities and the verification of the compliance and effectiveness percentages evaluated in each heading. If the necessary learning percentages are met, the system terminates the process. If it does not meet the condition, feedback is made and the process is sent to the data analysis stage. At this stage, the data will be analyzed and new data that complements the results will be deleted or added.

Table 4 shows the process of recommendation of activities; this process performs the AI module with each of the students. The module establishes the weights through which it performs the calculations to reach a certain conclusion. Weights are determined through five unique probability values that are, 1 = satisfactory, 0.75 = very good, 0.50 = good, 0.25 = insufficient, 0 = no. This allows the student's learning to be measured according to measurable criteria and the activities carried out. For example, to identify the tasks that are recommended for students who have limited time in the development of activities, the system eliminates activities that do not meet these criteria by recommending the activities with greater weight. For students who meet the conditions indicated after performing the process and calculation, the system will recommend the rapid test activities that are an optimal activity. In addition, the Chatbot recommends the student to develop activities such as recreational games and concept maps that have a lower weight, but the student gets variety in the development of activities.

In this case, there are several activities that a student has done and the weights he has obtained in each of the criteria. According to this data, the Chatbot can easily identify which activity aligns with the student's needs. For the choice of criteria and activities, a very small sample has been chosen since the Chatbot architecture and its operation is more complete and complex, since it counts on the interaction with the user and these parameters can change according to the needs.

Table 4. Recommendation of activities through the process of weights in the learning criteria.

Criteria	Reading Control	Rapid Tests	Playful Games	Case Development	Discussion Forums	Conceptual Maps
Limited time in the development of activities	0	1	0.75	0	0.5	0.75
Easily capture the idea	1	0	1	0.75	1	1
Solve problems and learn	0	0	0.75	1	0	0.75
Debate on specific topics	0	0	0	0.5	1	0.75
Constant review	1	0	0.75	0	0.25	0
What do I understand	0	0.25	0.75	1	0	1
I talk with other people and I understand	0	0	0	1	0	0.75

5. Discussion

This work proposes an architecture that integrates several systems that are responsible for much-needed tasks in the educational field. These tasks range from data analysis to the integration of AI within an LMS context. An architecture with these characteristics allows improving learning by integrating the whole process in a cycle where learning focuses on the needs of the student. Each of the stages in other works are established as individual tools that contribute to the development of student learning. However, the strength of the proposed architecture allows the acquisition and analysis of data from various sources where relevant information on student performance is included. Integrating a data analysis system into the architecture is possible by using ETL processes that allow establishing connection strings with different databases.

This process ensures that the data included in the analysis is of quality, adding reliability to the following phases. The clean data that is analyzed by various data mining algorithms identify patterns in the data through which it is established such as what are the strengths and weaknesses in each student's learning.

Once the weaknesses of each student are established, these results are sent to an AI system. The difference between a normal educational data mining method is that decision-making and actions always depend on the people in charge of learning. This is a weakness in the process since no matter how much a previous analysis exists, the final action depends on the criteria of a person. Another disadvantage is that each action to have an effect must be performed immediately. This is a process dependent on people which is not possible because of the number of students belonging to a university. The proposed system contributes significantly to this process, by integrating an AI module that allows real-time decision-making. The module has the information resulting from data analysis and the interaction of the Chatbot with the user.

The inclusion of an artificial AI model in learning, as well as new models that involve technology, are often considered as the intrusion of totally technical areas in pedagogical matters. However, technology is currently necessary to solve problems caused by the evolution of educational models. For example, the educational trend is to migrate face-to-face education models to online educational models. These models must necessarily include ICT as an ideal assistant for teachers and academic areas. Generally, in the online models, students and teachers do not get to know each other personally. This returns to the learning environment in cold models where the student makes his best effort to understand what he wants to learn and the teacher makes the possible to understand the problems of your students. Creating tools, such as the one proposed in this work, adapts to any educational model where student interaction can develop at any time without natural limitations on a person. In addition, having the knowledge of all the needs that the student has uses their historical potentials to find better solutions.

6. Conclusions

New technologies must necessarily be coupled to existing educational models and should serve as axes for the creation of new models. This system, when created with a generic model in mind, seeks to engage in face-to-face, semi-presence or online education models. This system helps in the student follow-up, that by having an AI module learns from each interaction with the user and adjusts their weights that improve the understanding of natural language and the conclusions it reaches.

The inclusion of a comprehensive system that includes data analysis, decision-making through AI and the recommendation of activities in an LMS environment allows for a marked improvement in learning. The deployment of a data analysis platform that is responsible for the processing of academic data allows students to learn more about trends, strengths and weaknesses. However, the scope of this work is fully scalable which means that the system allows adding other actors in the field of education, for example, the system can become the ideal teacher assistant and even more in the administrative development of university.

Decision-making is one of the strongest points and with the greatest consequences both in an academic environment and in the industry. However, this must be effective and efficiently executed at the right time, as in the development of learning this takes greater value. Moreover, on this depends the academic success or failure of the students. This is accompanied by constant monitoring of the student and all the academic activities he or she performs inside and outside the classroom.

Entrusting this activity to an AI module is the closest thing to managing a tutor at all times. This is responsible for notifying all the activities that the student must develop, and their chances of interacting with the student improve their interest in the subject to the point that the AI can recommend that activity aligns with the needs and ways of learning of each of the students.

The inclusion of an AI model through a Chatbot responds to the needs of the students of a smart campus. Needs are part of an analysis of several works that reflect studies on learning theories. In these theories, learning is treated as a cause of the identification of the typical problems that students encounter in the development of academic activities. The use of learning through activities responds to variables and patterns that can be found in a group of students. However, this does not imply that these variables do not allow students to be evaluated individually. The evaluation and identification of weaknesses individually is what allows models such as AI to be used to personalize learning.

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