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Intelligent personal learning environments as support for inclusive education at the higher education level

Entornos personales de aprendizaje inteligentes como soporte para la educación inclusiva en el nivel de educación superior

Julio César Enríquez-González[1], Jaime Muñoz-Arteaga[1],
José Rafael Rojano-Cáceres[2], Víctor Hugo Menéndez-Domínguez[3]

[1] Universidad Autónoma de Aguascalientes, México
[2] Universidad Veracruzana, México
[3] Universidad Autónoma de Yucatán, México

julioc.engon@gmail.com , jaime.munoz@edu.uaa.mx , rrojano@uv.mx ,
mdoming@correo.uady.mx

ABSTRACT. Currently, due to the United Nations (UN) Agenda 2030 specifically goal 4 focused on education, higher education institutions (HEI) are striving to address inclusive education in the best possible way, it is a pending issue that is on the agenda of HEI educational policies. Personal learning environments (PLE) are educational technologies that are ideally suited to support the implementation of inclusive education because they provide a personalized learning space for each student. Machine learning techniques are used to process students' academic information and thus detect patterns of information in the data. This study has as a priority to present at an architectural level a Personal Learning Environment that integrates a Federated Learning model and through the students' data interaction this way is possible to know the learning needs of each one with the help of Universal Design for Learning (UDL).

RESUMEN. Actualmente, debido a la Agenda 2030 de la Organización de Naciones Unidas (ONU), específicamente el objetivo 4 enfocado en la educación, las instituciones de educación superior (IES) se esfuerzan por abordar la educación inclusiva de la mejor manera posible, es un asunto pendiente que se encuentra en la agenda de las políticas educativas de las IES. Los entornos personales de aprendizaje (EPA) sirven de apoyo para la implementación de la educación inclusiva porque personalizan el aprendizaje. Las técnicas de aprendizaje máquina procesan información académica de los estudiantes y detectan de esta manera patrones de información en los datos. Este estudio tiene como prioridad presentar a un Entorno Personal de Aprendizaje que integra un modelo de Aprendizaje Federado y a través de datos de interacción de estudiantes, de esta manera se pueden conocer las necesidades de aprendizaje particulares de cada uno con el apoyo del Diseño Universal para el Aprendizaje (DUA).

KEYWORDS: Inclusive education, Universal design for learning, Federated learning, Personal learning environments.

PALABRAS CLAVE: Educación inclusiva, Diseño universal para el aprendizaje, Aprendizaje federado, Entornos personales de aprendizaje.

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1. Introduction

The United Nations (UN) 2030 Agenda has as goal number 4 the education sector, which aims to achieve equitable educational opportunities for all people, with special emphasis on marginalized social groups (Aguirre-Bravo et al., 2023). In Mexico, a novel legislative framework related to higher education has been designed, which guarantees equitable standards for all university students, mainly students from vulnerable populations (Sánchez-Lissen & Sianes-Bautista, 2021).

Information and communication technologies (ICT) have established a significant association with education and its processes, functioning as instrumental tools to facilitate advances in the educational field (Tejo et al., 2024).

The application of artificial intelligence (AI) represents a technological advance that facilitates the implementation of inclusive education in HEI; in particular, federated learning is a type of machine learning designed to address security issues effectively (Szwed, 2023).

A personal learning environment (PLE) constitutes a methodology for customizing educational technologies to suit the unique learning needs of each learner, to increase the level of autonomy in their self-regulated learning processes (Valencia et al., 2024).

Using and managing students' academic information, teachers and higher education institutions (HEI) can make more accurate data-driven decisions to address students' learning needs within the context of inclusive education (Chen, 2020). On the other hand, (Hills et al., 2022) mentions the need to encourage all those involved in the teaching-learning process to a greater understanding of the learning deficit at the university level, from the point of view of the universal design for learning (UDL), it is the academic program that should be adjusted to the needs of each student and not the other way around. Considering PLE and federated learning models as technological tools and UDL as the pedagogical one, this paper focuses on the feasibility of supporting the implementation of inclusive education at the higher level.

The following is the structure of this document: Section 2 presents the definition of the fundamental concepts. Section 3 provides information on the problem statement. Section 4 presents an architectural model of an intelligent personal learning environment. Section 5 shows the conceptual model for federated learning applied in HEIs from the perspective of inclusive education. Section 6 explains through a scenario how both models address and solve the problem of this research. Section 7 describes the steps from methodology to carry out the training test of federated learning model. Section 8 is used to show results of this research. Section 9 provides a space for the conclusion of this work. Section 10 acknowledgments to realize this research.

2. Literature review

2.1. Inclusive education

Just 300 to 350 years ago, people with some type of physical and/or intellectual impairment were practically impossible to access even basic levels of schooling (Chávez et al., 2022).

During the period of the pandemic, the obstacles faced by students with disabilities participating in eLearning formats necessitated the utilization of at least one form of assistive technology; in the absence of teacher support, the level of accessibility and engagement experienced a notable escalation for this group of students (Wilkens et al., 2021).

Currently, higher education students face a list of deficiencies in their academic environment: lack of personalized and inclusive pedagogical design, rigid curricula, standardized teaching-learning paradigms, and so on (Fierro-Saltos et al., 2020).

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Despite exists a genuine inclination among numerous universities to accommodate students with disabilities; nevertheless, ensuring the successful graduation of this students' group remains an unresolved challenge, attributable to the elevated attrition rates observed within this population (Moriña et al., 2020).

Education in general has evolved only to favour regular students, this has generated a social and pedagogical debt for the student population that demands inclusive educational needs (Díaz & Betancourt, 2022).

2.2. Universal design for learning

A definition of universal design for learning (UDL): "It is an approach designed to provide equal opportunities for students with disabilities to learn in inclusive environments, through flexible curricular approaches, within the framework of human rights-based education" (Comisión Nacional para la Mejora Continua de la Educación [Mejoredu], 2020).

UDL is underpinned by a set of standards that can be incorporated into almost all learning environments, the implementation of UDL is about content and supports various forms of instructional design (Basham et al., 2020).

UDL has three general principles: multiple means of engagement, multiple means of representing content, and multiple means of expressing knowledge understanding. These principles are intended to minimize the challenges faced by the population with inclusive educational needs in the classroom (Sasson et al., 2021).

Besides (Roski et al., 2021) mentions that UDL is based on a set of guidelines that can be incorporated in almost all learning environments, the implementation of the UDL is related to the contents and supports several forms of instructional design, also is considered what most educational systems are underusing technological resources to address the learning diversity of student effectively.

2.3. Ethical and privacy considerations

Both (Atarah et al., 2023) and (Zhang et al., 2021) agree that it is critical to pay attention to ethical and safety issues in the process of collecting, using, and disseminating students' academic data when working with AI.

AI can make poor decisions that negatively affect ethical issues related to the human rights of students, so AI should not be given absolute "freedom" in the educational context (Nalbant, 2021).

(Mogiaku et al., 2023) identify the main ethical considerations to be considered with the use of student data:

- Privacy: is the regulation on how personal digital information is observed by oneself or distributed to other observers.
- Ownership: is the act of having legal rights and full control over a data set.
- Consent: refers to the acceptance of the processes involved in data collection and analysis.
- Transparency: is the control over the purposes for which data will be collected and used.

2.4. Personal learning environments

The most compelling argument for a PLE is to be able to create educational technology that meets the learning needs that people require to shape their own learning environments (Atwell, 2023).

PLE are seen as a new way to facilitate the generation of learning spaces where students develop diverse digital skills (Pereira-Medina, 2021).

The implementation of a PLE is based on the principles of self-regulated learning, having personalized information in a learning space is relevant because these data help students to achieve their academic goals (Merla-González et al., 2021). Also, PLE serve as the technological educational space for learning that extends beyond the confines of higher education, thus providing technological assistance for continuous lifelong learning endeavors (Serrano-Sánchez et al., 2021).

PLE must cater to the educational requirements of learners; additionally, the PLE ought to facilitate engagement between the educator and their colleagues, systematically arrange their preferred study applications, and effectively oversee their academic resources, thereby enhancing the students' access to an enriched educational experience (Dabbagh & Kwende, 2021).

2.5. Federated learning

A definition of federated learning: "is a learning paradigm that seeks to address the problem of data governance and privacy by collaboratively training algorithms without exchanging the data itself" (Rieke et al., 2020).

Federated learning is a new machine learning paradigm whose main characteristic is that it is decentralized and runs on n nodes connected to a server (Song et al., 2020).

There are two main architectures for federated learning models: cross-silo also called vertical, and cross-device also called horizontal (Fachola et al., 2023).

It is designed to improve the results obtained with the use of centralized machine learning, since through the sum of the training results of n nodes on a main server, the results are better (Chu et al., 2022).

Is Considered a useful technology able to track the knowledge generated by students based on their academic information. This feature is essential for so-called intelligent education (Wu et al., 2021).

3. Problem outline

It is considered that efforts to implement inclusive education at the global and national levels are not sufficient. There are several factors that can be improved to integrate inclusive education at the higher level.

The gap between institutions and the use of digital learning materials is evident; although digital access to them is available, their use is not the most effective (Monjelat et al., 2021).

A significant number of educational technologies and resources were designed in a standard way for the majority student population, without considering the inclusive educational needs of minorities.

The simple fact of the existence of any technology in an educational institution does not improve the teaching-learning process; other strategic elements are required, such as the implementation of pedagogical methodologies and the understanding of the student's social context, so that such technology can be applied effectively (Peltz, 2020).

It is necessary to design an educational model that integrates the diversity of educational needs, teacher training, technological infrastructure and sufficient digital educational resources and digital educational resources to meet the inclusive educational needs of the entire student population (Valenzuela et al., 2020).

4. Architectural model of PLE

Before presenting the architectural model of this work, some commercial applications that are considered as a PLE are considered and some of their characteristics are described.

According to (Huerta, 2020) Symbaloo is a web application that brings together, in one place, various digital resources that each user considers significant, and it is possible to share them with their contacts. On the other hand, Start.me is a web platform where users can create a space where they can organize different types of resources (Start.me, 2024). Pearltrees is an ICT-based service that can be used to generate a PLE, adding several digital resources to the same site (Aula Planeta, 2024). Another application that can be considered a PLE is Padlet, a web application that allows generating information boards, organized by type in

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a simple way for users (Padlet, 2024).

The applications presented have a common characteristic, they were not initially designed to be a PLE, they can be used as a PLE, however, each of the architectures of these applications is different from each other and not all applications have the same features and services. They also do not make use of AI for the benefit of their users.

In addition, such applications are aimed at the regular population, their designs do not consider accessibility and usability criteria to address inclusive education, and since they are third-party applications, external to HEI, the data collected by students do not have an institutional guarantee on the proper use of their data.

The reason for proposing an architectural model of a PLE in this research is that although there are several works in the literature, there is a lack of a personal learning environment that considers pedagogical, inclusive and intelligent aspects, which allows the academic profiling of students in a personalized way. Figure 1 presents an architectural model for a PLE that supports the requirements of inclusive education.

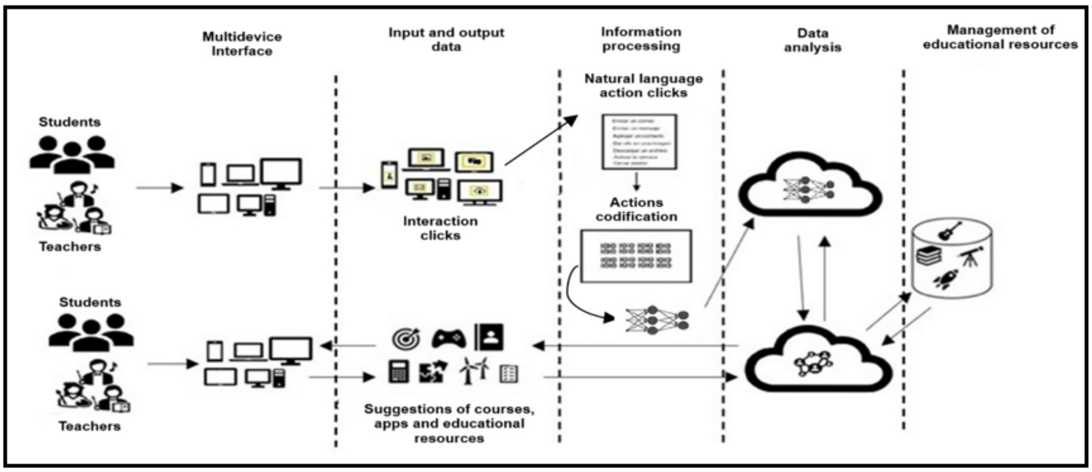

Figure 1. General architectural model for an inclusive intelligent personal learning environment. Source: Own elaboration.

The architecture of the model in Figure 1 is composed of five general layers, these layers are: multi-device interface, input and output data, information processing, data analysis and management of educational resources, it has a flow from left to right and from right to left.

This is due to obtaining data derived from the interaction of teachers and students with the PLE and the processing of these to later associate said information with the available educational resources, which are subsequently presented to each user according to their profile. What is intended with the architectural model proposed in this work is that teachers implement innovative teaching techniques so that, through flexible educational resources, user and learning experiences be generated for students that keep them in a learning process that awakens their interest in learning more on a continuous way.

Multidevice interface. This first layer of the proposed solution is the most important because it is where students and teachers will interact. For both users, the design of the interface and the ICT resources that are presented to each of them will be through a personal learning environment that meets their needs for access to information and educational resources ideally based on a recommendation of the PLE.
Input and output data. At this level of the proposed solution there is an input module whose main objective is to track the academic data of students in relation to their predominant or main type of intelligence according to multiple intelligences theory, their preferences in the use of certain types of digital resources, etc. To generate input parameters for the federated learning model.
Information processing. The main objective of this layer is to transform the interaction activities of teachers

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and students, from natural language to coding actions. This process is necessary to convert the information provided by PLE users so that it can be understood by the federated learning model.
Data analysis. This phase of the proposed solution is the most important, from a technical point of view, this level of the architecture contains the data management module and thanks to this element of the solution it will be possible to associate the information of each student and their learning needs in relation to their individual profile and the needs for accessibility to information and educational resources based on ICT that adapt to said personal needs.
Management of educational resources. In this layer of the proposed solution there will be the repositories with the information on the student profiles, as well as the repositories of educational resources for the majority student population and educational resources for students who present some type of learning deficit. It is important to mention that free license requests and digital materials will be stored in both educational resource repositories.

5. Model for federated learning

As part of this study, we randomly selected some works like the one proposed, where a federated learning model is used in the educational sector and that have common issues such as student data tracking and ethical issues with the use of academic data.

In the work of (Zhang et al., 2024) the aim is to improve the process of predicting learning outcomes; therefore, they present a distributed grade prediction model called FecMap that works in local learning spaces and has multilayer privacy protection. In the research of (Rani et al., 2024) the goal is to improve the tracking of student activity on learning platforms, by accessing the information that students generate when interacting with digital tools, without violating student privacy, a pioneering approach is presented that combines screen tracking techniques and the security, privacy and protection feature of federated learning. In the study by (Zhang et al., 2023) the identification of learning patterns that contribute to predicting student dropout rates with a centralized approach to data access is a limitation to ensure generalizable and reliable results. The authors present the Federated Learning Pattern Aware Dropout Prediction Model (FLPADPM). Finally, in the work of (Sekhar et al., 2024) effective tracking of student learning outcomes and activities is achieved, a framework based on federated learning is proposed that is capable of tracking learner activities.

Although the related works make use of a federated learning model in the educational sector and some of them mention that they follow up on the interaction of user activities in eLearning platforms, no one point out that such efforts consider the implementation of inclusive education. Federated learning is a growing modern artificial intelligence. This machine learning paradigm is quite useful to train an intelligent model that can personalize the educational needs of each student.

An advantage of implementing a federated learning model is that for its training, parameters useful for the analysis of the interaction of students with the digital educational resources they use in their academic training are specifically used, so that sensitive data remain in each of the nodes, without being shared with the entire model. After conducting training of the model, the model will be able to suggest ICT-based educational tools according to the preferences and learning needs of each learner that will support each learner and enhance their experience with the learning environment and the suggested applications.

A federated learning model is presented in Figure 2. This model is based on the cross-device federated learning architecture. From bottom to top, it can be observed how students interact with PLE, through different devices. It is relevant to mention that, in this federated learning model, each device of each student is a node that provides information to the whole federated learning model.

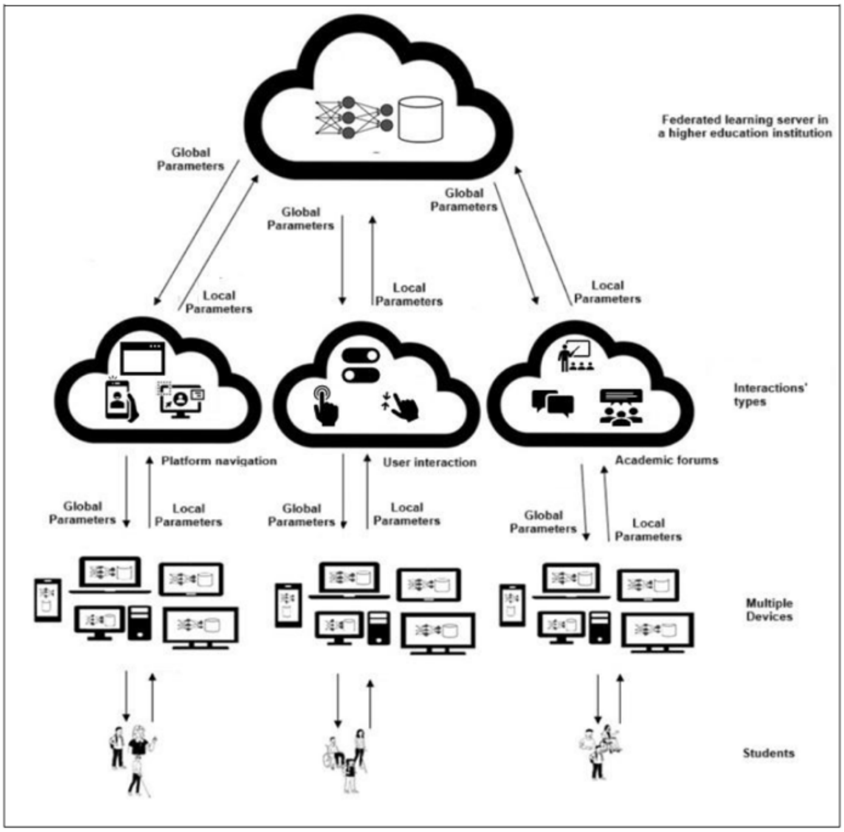

Figure 2. General model of Federated learning, as technological tool to support inclusive education. Source: Own elaboration.

This information is processed by the main server, in each device the PLE user interface is presented, the interface is made up of a set of educational content that meets the learning needs of each student for each of their subjects.

It can also be observed that each subject is taught by a teacher, in the context of the federated learning model, the role of the teacher is very relevant, since he/she is in charge of managing, channeling and developing the individual educational resources, finally at the top of the model is the main server of the HEI, where the general learning model is stored, which receives, processes and aggregates the information sent by the devices of each student. Thanks to the results obtained through this model it is possible to generate different user interfaces for a PLE according to the profiles of each student.

Besides the PLE architecture and federated learning model, as final part of the conceptual contribution of this study is to propose variables that belong to a set of useful data to be able to achieve the conceptually proposed in relation to the identification of the learning needs of each student through the models presented in this research, as a technological solution to implement inclusive education at the higher level. Table 1 presents a proposed set of variables that can be used to train the federated learning model shown in this paper.

Variable	Description
Device type to access PLE	Identify favourite or most used device as educational support to work with PLE
Session schedule	Schedule preference to access PLE
Session time	Total invested time in PLE
Content type	Format in which an educational topic is presented

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Variable	Description
Total clicks on content	Total number of clicks on educational content
Content use time	Total time of use and interaction with a content
Content evaluation	Content evaluation by students
Messages sent to the teacher	Total number of messages sent to the teacher
Messages sent to partners	Total number of messages that students sent to each other
Auto learning activity type	Format in which the self-learning activity is presented
Total time to finish auto learning activity	Total time each student requires to complete a self-study activity.
Web sites	List of URLs visited by each student.
Search keywords	Set of keywords for each student
Course evaluation	Overall rating of each student of an online course

Table 1. Proposed data set. Source: Own elaboration.

For (Domínguez & Ruipérez, 2020), (Klasnja-Milicevik, et al., 2020) and (Mian et al., 2022) through learning analytics (LA) HEI access large amounts of useful data to understand how the teaching-learning process works between teachers and students to improve student performance. Another goal of LA is to make suggestions based on learner profiles about educational resources (Hamal et al., 2022). Descriptive analytics perform common statistical analysis, diagnostic analytics focus on previous information, and predictive analytics use the data to estimate new information (Contreras-Bravo et al., 2021).

6. Scenario of proposed intelligent PLE

To apply the models proposed in this research, the following scenario is presented, teacher López is a full-time professor in the Departamento de Sistemas de Información at the Universidad Autónoma de Aguascalientes (UAA). This semester she teaches the subject of programming logic to students in the Computer Systems Engineering (CSE) program. This is a group of 37 students and in this group, there are three students with learning deficits: Maria Gómez, Luis González and Aldo Canales. Aldo has a moderate hearing problem in both ears, Luis lost his right hand and arm in an accident when he was a child, his motor level is considered intermediate, Maria has low vision, which has been increasing throughout the semesters at the university, her level of low visibility is still moderate, but she decided to learn Braille.

Table 2 shows some general indicators related to the learning process of Maria, Luis and Aldo: accessibility support, level of interactive dependency, meaningful learning and failure rate, to name a few. These indicators currently at UAA, without the implementation of the solution proposed in this work through the federated learning models and the PLE architectural model, suggest that these three students have high probability of failing this and other subjects and there is even the possibility that they will not conclude their higher education studies.

Students	Learning deficit	Learning indicators	Values
María	Low vision	Accessibility support	Partners and teacher
		Interactive dependency level	High
		Meaningful learning	Very few
		Probability of failure	High
		Interest for learning	Low
		Possibility of defection	Very high

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Students	Learning deficit	Learning indicators	Values
Luis	Low arm and hand motor skills	Accessibility support	Partners and teacher
		Interactive dependency level	Medium
		Meaningful learning	Medium
		Probability of failure	Medium
		Interest for learning	Low
		Possibility of defection	High
Aldo	Moderate hearing loss	Accessibility support	Partners and teacher
		Interactive dependency level	Medium
		Meaningful learning	Medium
		Probability of failure	Medium High
		Interest for learning	Medium Low
		Possibility of defection	Medium High

Table 2. Learning context prior to applying the proposed model. Source: Own elaboration.

In order to provide technological support to these students in relation to their individual learning needs, an instance of the model in Figure 1 is implemented, but now, with real current elements, applications and resources available at the UAA, as well as prototype interfaces, designed to exemplify each of the modules that make up the model so that these three undergraduate students can access the online course of Ms. López with the best possible conditions in accordance with inclusive education. The first layer from PLE architectural model has implemented the three main UDL principles to guarantee an accessible, usable and inclusive interface. The architecture of this instance can be seen in Figure 3.

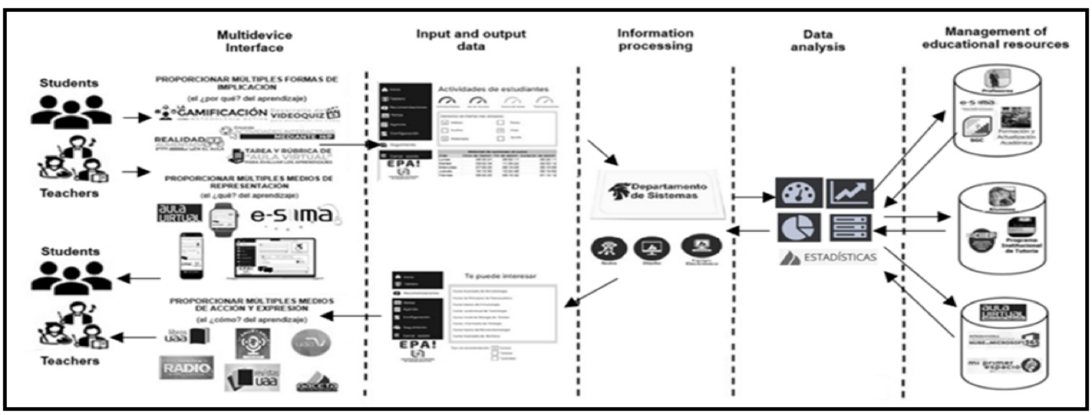

Figure 3. Applied architectural model for the UAA scenario. Source: Own elaboration.

Figure 4 presents an instance of the proposed federated learning model with UAA students, professors and applications. Through the federated learning model, data can be obtained to associate these needs with the ideal digital educational content so that the entire student population is in a context of equity and equality, in terms of accessibility and use of these resources so that their learning is meaningful.

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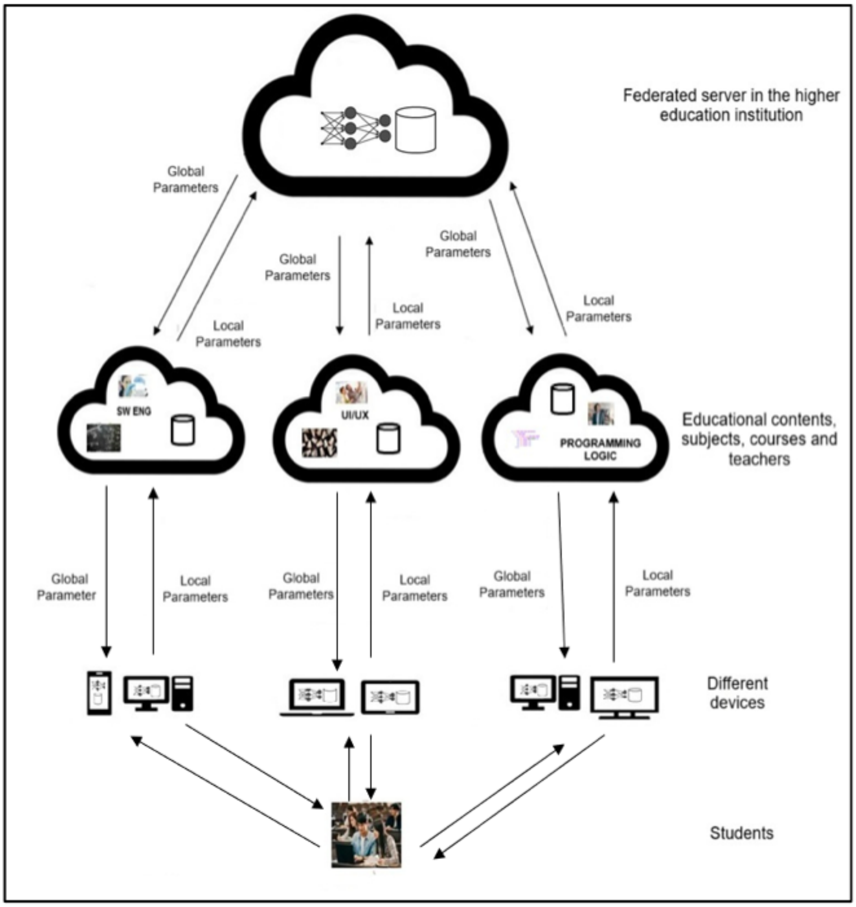

Figure 4. Applied federated learning model for the UAA scenario. Source: Own elaboration.

Software engineering cloud and UI/UX cloud are there just as an example, point out that college students take different subjects, with distinct teachers, several complexity levels and a diverse kind of challenges to each subject.

Table 3 shows how the negative learning indicators such as the possibility of not accrediting or the possibility of not concluding their degree, improved after the implementation of the models proposed in this research at the UAA.

Students	Learning deficit	Learning indicators	Values
María	Low vision	Accessibility support	NVDA screen reader
		Interactive dependency level	Low
		Meaningful learning	High
		Probability of failure	Low
		Interest for learning	High
		Possibility of defection	Null
Luis	Low arm and hand motor skills	Accessibility support	Biogrip system
		Interactive dependency level	Low
		Meaningful learning	High
		Probability of failure	Very Low
		Interest for learning	High
		Possibility of defection	Null

Students	Learning deficit	Learning indicators	Values
Aldo	Moderate hearing loss	Accessibility support	uSound audiometer
		Interactive dependency level	Low
		Meaningful learning	High
		Probability of failure	Very Low
		Interest for learning	High
		Possibility of defection	Null

Table 3. Learning status after the implementation of proposed model. Source: Own elaboration.

After the implementation of the models proposed in this study, the indicators of the learning process of Maria, Luis and Aldo have improved significantly. Maria has reached a high degree of self-confidence, her dependence on her peers has decreased, she has achieved a better level of educational independence with the support of the NVDA application and other content magnification tools, and she wishes to continue and conclude her university career. Luis, with the use of the BioGrip application in his PLE, can work in a "natural" way with his prosthetic right arm and hand, his mood has improved, and he is now confident of becoming a professional software developer. Aldo with the help of the uSound application has also improved his academic performance, not only in the programming logic subject with Ms. Lopez, but in all the other subjects, now he feels good about himself and accepts in the group, without any doubt he is becoming a successful computer systems engineer.

According to Table 2 negative learning indicators such as: Level of interactive dependencies, probability of failing, possibility of desertion with high values for each of the three students with inclusive educational needs in the scenario raised, after the PLE architectural model that integrates the federated learning model is implemented, such learning indicators, according to Table 3, now have low values, That is to say, it is unlikely that these three students will fail their subjects and even worse that they will decide to leave their degree unfinished, their level of interactive independence also decreases on the part of their classmates and professors since now Maria, Luis and Aldo have a specific assistive technology that allows them to have greater independence in their academic activities.

Similarly in Table 2 some of the positive learning indicators, for Maria, Luis and Aldo, present low value, namely: meaningful learning and interest in learning. But after, in the case of these three students, as shown in Table 3, these learning indicators now have high values as shown in Table 3. That is, these three students, by interacting with personalized content and resources tailored to their specific inclusive educational needs, learn in a better way, thus increasing their interest in learning and achieving more meaningful learning.

As stated in this section, at this time it is only a scenario of application of the PLE architectural model and the federated learning model, however, it is required to carry out a real test of what is proposed in this work.

The methodology to be followed is as follows: develop a simple but accessible interface for students that allows monitoring the websites they visit, the keywords they type in the browser, detect which are the applications they use most for the development of their academic activities, identify what type of content and evaluation activities they prefer, etc.

The objective is to obtain this information for each student so that it is sent to the federated learning model server. Based on information of each student's interaction, the federated learning model will generate recommendations for each student.

7. Methodology

To evaluate the proposed solution, teacher López and other three Programming Logic teachers are part of the test. Programming Logic is offered online in the first semester to Computer Systems Engineering students. The cohort is divided into four groups: A, B, C and D, with each group consisting of 20 students. Each group is assigned a specific instructor: teacher López teaches Group A, teacher Pérez handles Group B, teacher González leads Group C and teacher Tagle oversees Group D.

The course has common contents such as videos, pdf files, audios, images, animations, etc. It has frequent activity types such quizzes, memory games, and relation columns, open question tests, etc. Also, the course has two forums, one where students can ask their teachers any question, and other forums where each student can interact with their peers without the teacher.

The conceptual proposal presented in this work focuses on three and four layers, Information processing and Data analysis, respectively from PLE architecture. To train the federated learning model it was necessary to generate a synthetic dataset with information about students' interactions in the Programming Logic online course. Dataset values are measured in time units, number of messages from students to teacher and from student to student, and in the number of clicks from a user over a content or an activity or while is navigating in the platform.

Students' interactions with the programming logic online course represents in the case of unit times, the minutes that a student requires to watch a video and understand a specific topic, or the employed necessary time that a student needed to finish an activity, the time that each student invests in navigating in the online course platform could be useful information about students' digital skills level.

In the case of the number of clicks, that means how many times a student downloads a pdf file, or how many times a student played an audio file, number of clicks also gave information about how many times a student tried to solve a particular activity. When a teacher provides the students with any type of content and assigns any type of activity, the teacher expects that all students interact with those two elements without problem, however less or a greater number of clicks in a content or in an activity.

However, it could be possible that the student would click too many times that content because he didn't have a good internet connection or because that content wasn't completely clear. To know if a specific number of clicks of each a good result is or is a bad result, is fundamental to have some standard data to compare with.

And about the number of messages between teachers and students, this measure offers information about how dynamic the course is, in an environment where students can participate mostly by asking questions of the teacher and between them and if the teacher can answer students' doubts. In an online learning course, communication media is fundamental for a good course development, this way teachers and students eliminate the distance barrier and help all the group to demonstrate themselves that to work and participate as a team is possible.

It's important to mention what students attend and interact with the online course from different operating systems like Windows, Linux, Mac, Android, etc. Different browsers like Chrome, Mozilla, Brave, Safari, etc. And different electronic devices such smartphones, tablets, laptops, desktops, etc.

The objective is to train the proposed federated learning model in this work using a synthetic dataset representing student interaction in an online course on programming logic. Using within the federated learning model the K-Means algorithm will help to determine clusters of students based on their interactions with the online learning course in order to identify similarities among the students' profiles and thanks to this cluster try to answer questions like which are the contents most used by students and of what type, how much time do students invest in using content?, how much time students invest to finish activities and which are most useful for the students? how many questions students ask to their teachers? how many messages students send between for academic and collaborative goals? etc.

8. Results

To help readers to understand the results, before presenting them, it's considered pertinent to share a little information about K-means algorithm and the Davies Bouldin Index, with this information it expects that obtained results make more sense.

Within eLearning, the K-means algorithm can be used to group a set of learners in relation to their participation in an online course and based on their learning behavior in the course. The K-means algorithm is considered a modern machine learning technique used to create groups of learners with similar eLearning course results, based on mean and standard deviation statistics to observe how the learners' grades are distributed (Tuyishimire et al., 2022). The K-means algorithm divides the dataset into clusters, each cluster has a centroid, and all the data has a centroid and all the data that resembles the value of a certain centroid are associated to that group (Moubayed et al., 2020).

The David-Bouldin index (DBI) evaluates a dataset with respect to its compactness and separation. The formulation of the DBI is predicated on the relationship between the dispersion within clusters (intra-cluster) and the separation among clusters (inter-cluster) (Geeks for Geeks, 2024). Specifically, intra-cluster dispersion quantifies the separation of data points within individual clusters. A minimal intra-cluster dispersion signifies that the data points within a specific group are near one another, which is a favorable characteristic of effective clustering. Conversely, intercluster dispersion assesses the separation between different groups. A substantial inter-cluster dispersion implies that the groups are distanced from one another, which is likewise a desirable attribute in effective clustering. The DBI is formulated as the ratio of these two calculated values. Therefore, when clusters exhibit both separation and compactness, the value of this index is minimized (Analytics Lane, 2024).

Reduced values of the DBI are indicative of superior clustering quality. A DBI nearing 0.79 signifies commendable clustering quality. Diminished DBI values are preferable, and within this framework, a value beneath 1 implies that the clusters exhibit effective separation and compactness. Considering information about DBI datasets to each group, they were divided into three interaction types: platform navigation, activities and academic forums (Medium, 2024).

Once having information about K-means algorithm and David-Bouldin Index, now obtained results are shared. According to the A, B, C and D groups and their own respective data these four groups share students' interaction data of the online course through platform navigation, user interaction and academic forums. After data were processed with K-means algorithm, some results are presented next.

Using the K-Means algorithm in a federated context, dataset variables to each type from group were processed and after three rounds DBI values were obtained to each interaction type and for all the groups, the goal to this test is to see what the data behavior from programming logic groups data is (A, B, C, D) in relation with DBI scores. It's important to know if cluster from groups' data is well defined or not.

About students' learning activities interaction type, variables from this kind of interaction are learning activity type and learning activity duration. Values from learning activity type could be crossword, columns relation, open questions, etc. And values from learning activity duration could be 10:10 minutes, 9:40 minutes, 11:20 minutes etc. In Table 4 DBI results from learning activities interaction are presented.

Round	David-Bouldin Index (DBI)
1	0.8150406547099429
2	0.7749132688749045
3	0.7815714520889471

Table 4. DBI results from learning activities interaction. Source: Own elaboration.

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Based on (Medium, 2024) DBI results from activities interaction in the last round is 0.78 very near 0.79, that means that there exists a good quality in clusters formed to this data from four groups.

Most students, if possible, all should find activities useful and interesting, activities should be easy enough to solved, so students felt comfortable doing those activities, without presenting any kind of digital distraction. They should focus on solving their learning task.

Navigation platform in this case refers to contents in the programming logic online learning course mainly but also consider the main interface of the PLE and any other kind of digital element that can be used for students in their learning process. The two variables from this interaction type are content type and content duration. Values from content type could be a pdf file, a video, a podcast, an image, etc. On the other hand, content duration has values like 8:30 minutes, 9:10 minutes, 10:30 minutes, etc. In Table 5 DBI results from contents interaction are shown.

Round	David-Bouldin Index (DBI)
1	0.8502598678553012
2	0.8442216072370062
3	0.826177301870872

Table 5. DBI results from contents interaction. Source: Own elaboration.

In the case with DBI results from platform navigation, DBI scores are a little higher than 0.79 value taken (Medium, 2024). This could significates that K-Means algorithm found a little trouble to generate clusters with this interaction type data. Anyway, those results are under 1 value.

From perspective to UDL it is important to know if a content helps students with their main goals, of the day, of the semester and even for the life. The contents should be enough intuitive and practical, should really support students with their learning process. If educational content isn't useful in that way, it is possible that there exist learning barriers between students and the educational contents.

Academic forums variables are professor messages and students' messages; the first variable stores values related to the number of messages that each student sends to the teacher and the second one stores values about the number of messages that students share during the online learning class. Values from professor messages are 3, 0, 1 etc. Values from students' messages could be 0, 3, 2 etc. In Table 6 DBI results from academic forums interaction are presented.

Round	David-Bouldin Index (DBI)
1	0.71377064565392203
2	0.77547562420399987
3	0.7321773749612297

Table 6. DBI results from academic forums interaction. Source: Own elaboration.

Finally, DBI scores from academic forums presents as final value of third round of 0.73, these results are minor than 0.79 from reference (Medium, 2024), that means this interaction data type is a good result too, even better.

It is very important that there exists a way to communicate students and teachers in an online learning course. This service should be very friendly and striking to the students, because these features are well valued by students, this feature implies security and confidence to ask their teachers to their teachers.

Teachers are interested in providing answers to their students' questions and whether the answers are

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useful for them. Under a UDL approach teachers also can realize which students feel more secure and comfortable to participate in the teaching-learning process.

These results obtained after federated learning process are considered relevant, because formed clusters in each interaction type of data could be used to identify similarities between students' interaction behavior. Through data processed in a federated learning model to each student and its interaction behavior, that information will help to detect how contents, activities and message communication services make students feel free from any type of learning barriers in their learning process supported by educational technologies and the UDL approach.

9. Conclusions

Federated learning offers some benefits and advantages in comparison with the classical machine learning approach, one of the most important characteristics is related to privacy and security while sensitive information is processed in this machine learning paradigm.

Another advantage is that federated learning can handle big amounts of data, due to n clients could be connected to a server. Whit that features in mind, the scenario is presented to explain why it is important to know how much time in average, students spent in different interaction types in an online learning about programming logic course.

For the scenery presented in this research, the K-means algorithm in a federated context was chosen as an example to show that with this algorithm and with others like random forest, decision tree and association rules, X-means, etc. Is it possible to identify students' behavior based on their interaction with an online learning course. For the scenario in this work four clients, in this case four groups A, B, C and D students interact with an online learning course about programming logic.

According to interactions data analysis, DBI results show that with the K-means algorithm, cluster from processed data of three interaction types got good results. This is a good advance because thanks to these clusters it is possible to analyze the similarities from those students who belong to each cluster. PLE are an example of ICT applied to education that allows a set of digital re-sources to be managed in the same space that serve as support for student learning, in this case PLE offers to students opportunity they have the control about how many apps they want to see in their main PLE interface, what kind of information they receive of courses, certifications and other interesting information for them, etc.

The idea is that college students feel comfortable with the available educational technologies provided by their institutions, in other words the goal is that they have a more autonomous and participative role in the learning process, without any kind of barriers according with UDL.

For future research, it is considered relevant to analyze in greater depth students' clusters, to identify in a more accurate way what students expect about the contents, activities and collaborative media to improve their learning experience and to achieve the digital wellbeing they deserve with the minimal but useful educative resources for them.

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