Education 4.0
A view from different digital proposals

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–Editors–

Editorial EAFIT

Education 4.0. A view from different digital proposals / Marta S. Tabares…[et al] ;
Cristian Suárez-Giraldo, Óscar Caicedo Alarcón, editores. –
Medellín : Editorial Eafit, 2020
112 p.; 24 cm. -- (Académica).

ISBN 978-958-720-701-9
ISBN 978-958-720-700-2 (versión web)

Tecnología educativa. 2. Innovaciones educativas. 3. Enseñanza con ayuda de computadores. 4. Procesamiento electrónico de datos en la educación. 5. Inteligencia artificial – Aplicaciones en educación. 6. Realidad aumentada en educación. I. Tabares, Marta S. II. Suárez-Giraldo, Cristian, edit. III. Caicedo Alarcón, Óscar, edit. IV. Tít. V. Serie

378.17 cd 23 ed.
E24
Universidad EAFIT - Centro Cultural Biblioteca Luis Echavarría Villegas

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Primera edición: diciembre de 2020

Carrera 49 No. 7 sur - 50
Tel.: 261 95 23, Medellín
Portal de libros: https://editorial.eafit.edu.co/index.php/editorial
http://www.eafit.edu.co/fondoeditorial
Correo electrónico: fonedit@eafit.edu.co

ISBN 978-958-720-701-9
ISBN 978-958-720-700-2 (versión web)
DOI: https://doi.org/10.17230/9789587207002lr0

Diseño: Alina Giraldo Yepes
Diagramación: Ana Milena Gómez C.
Corrección de textos y de prueba: Enago y Daniela Álvarez Yepes
Imagen de carátula: 1364078036, ©shutterstock.com

Universidad EAFIT | Vigilada Mineducación. Reconocimiento como Universidad: Decreto Número 759, del 6 de mayo de 1971, de la Presidencia de la República de Colombia. Reconocimiento personería jurídica: Número 75, del 28 de junio de 1960, expedida por la Gobernación de Antioquia. Acreditada institucionalmente por el Ministerio de Educación Nacional, mediante Resolución 1680 del 16 de marzo de 2010.

Editado en Medellín, Colombia

Contents

Preface

The development of new technologies, digital mediation, and the generation of new in-demand job offers, concerning industry 4.0 and the learning sciences, has impacted the education debate. How to educate future citizens in a permanently changing context and an increasingly rapid evolution? Both globalization and the new technologies, which have enabled other ways and platforms for social interaction and information access, shape a global environment in which education at all levels must play a protagonist role.

According to the World Economic Forum (2020) inform *Schools of the Future Defining New Models of Education for the Fourth Industrial Revolution*, eight crucial characteristics must be considered in the educational experiences and contents within the context of the Fourth Industrial Evolution: global citizenship skills, innovation and creativity skills, technology skills, interpersonal skills, personalized and self-paced learning, accessible and inclusive learning, problem-based and collaborative learning, and lifelong and student-driven learning (p. 4). This convergence between technical and human abilities in recognition of the singularities of the teacher and the protagonism of the students, conceived as agents of their learning, research, creative, and innovative processes, defines a perspective that modifies not only the educational models but the dynamics, the curriculum design and the disciplinary and professional focuses of high education programs.

In this sense, universities continue to play an essential role in society due to the education they give to the professionals who are going to work in job conditions, where the cyber-physical environments, the usage and decision-making through the harvesting and analysis of data, and the inclusion of artificial intelligence or the Internet in several processes are prevalent. Moreover, they take a primary part in the concretion of an ethical and civic conscience, which prepare students to face the cultural revolution that this new paradigm of production and socialization suggests, that must be paired with a cultural identity and global awareness, a scientific attitude and perspective, and a commitment to environmental sustainability, entrepreneurs and innovation leaders. The creation of new work profiles and innovative undergraduate programs, the adaptation of the curricular plans, the transfer of knowledge to the industry, and the flexibility of the teaching and learning through remote mechanisms and projects are actions that should be undertaken more frequently considering the Education 4.0 approach.

Moreover, universities should keep active the research projects on Education 4.0 and the several scenarios proposed by this, as Christopher Alan Bonfield, Marie Salter, Alan Longmuir, Matthew Benson & Chie Adachi (2020) posit:

> As we have noted throughout, on the one hand, more data and research are needed in order to redress the fact that efforts in the field of Education 4.0 are largely driven by intuition and common-sense extrapolations, rather than being solidly underpinned by research-informed models and frameworks. This will need to be evolved in light of the new approaches currently being trialed and perhaps in reaction to global shifts in the delivery of Higher Education post COVID-19. (p. 242)

This book is, then, a way to expose some research projects undertaken at the EAFIT University, in agreement with several technological companies, that develop three perspectives about education in a digital context, in which the informatic mediation and the use of technologies 4.0 lead the revision of the teaching and learning processes through a novel perspective.

The chapter "Toward the application of artificial intelligence in academic content: An autonomous recommendation system" presents a system that uses big data, data analytics, artificial intelligence to gather information and knowledge about digital resources on the Internet and recommend them to students and professors in blended or virtual courses. These digital resources are found and recovered using tags, descriptions, keywords, profiles, and preferences.

The second chapter, titled "Omnichannel for Learning", addresses the notion of omnichannel –a concept created in the Retail sector and later adopted by the educational sector–, which provides the student with a holistic view of the learning process. With this model, students are at the center of learning, allowing them access to different contents, conferences, and tutorships from any device, moment, and place. Furthermore, this research considers, due to the diversity of their resources, the utility of intelligent motors for educational purposes, within which lies the possibility of knowing the students' progress and their feedback needs.

Finally, in the last chapter, "Fostering intuitive knowledge of multivariable calculus concepts using a collaborative augmented reality", the authors describe the validation of an augment reality mobile application created to help junior engineering students to develop an intuitive comprehension of several multivariable calculus concepts, such as local maximum and minimum, directional derivatives, and intersections of surfaces and planes. The research demonstrates that the application is useful in the development of such understanding by the students.

Together, this book presents how 4.0 technologies enable a highly participatory and dialogic education, where students of different levels have the possibility of learning and training in their discipline while developing soft skills and, at the same time, the teachers can follow the development and evolution of these capacities and the purposes expected in the courses. Given the variety of courses modalities that are currently offered (e-learning, b-learning, m-learning, u-learning, among others), the applications presented in each chapter, as well as the appropriation of technologies for the enrichment of the students' cognitive and social skills, are an opportunity to explore new perspectives and approaches to Education 4.0.

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Toward the application of artificial intelligence in academic content: An autonomous recommendation system

DOI: https://doi.org/10.17230/9789587207002ch1

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The latest generation of new information and delivery channels is being produced at accelerated rates. This has made it nearly impossible to keep various courses updated (despite human intervention), which can limit the quality of virtual education and generate a systematic delay/gap in their learning processes. Thus, this project developed a system that uses big data analytics and artificial intelligence in order to gather information and knowledge from digital resources on the Internet, and recommend them to students and teachers in either blended or virtual courses. In this case, the digital resources mainly included texts and unstructured data (e.g., patents, articles, books, Wikis, etc.), audio and/or video, all of which can be difficult for processing and extracting value, information, and knowledge. It is important to note that such digital resources also support various courses by using tags, descriptions, keywords, logs, profiles, preferences, etc. Overall, the purpose of this project is to provide students and teachers with recommendations for the contents that best match their profiles and learning progress within each course.

This project, called Smart Contents (SmartCon), integrated many free sources and digital contents from the Internet in order to build a smart system that recommends the contents to different users in an educational context, based on big data analytics, autonomic computing, and artificial intelligence paradigms. This project included the following components: 1) identifying open, high-quality digital resources such as patents, articles, books, etc.; 2) harvesting these sources into a data lake; 3) processing and transforming these sources for the analytics stage; 4) building analytics models to enrich the knowledge of students and teachers as well as the contents of courses; 5) developing a search engine for all contents and knowledge, for further retrieval by the recommendation system; 6) defining the recommendation system, the main component of SmartCon, to personalize the contents to different users (e.g., students and teachers); 7) developing SmartLMS, an open-source learning management system (LMS) that uses the recommendation system through different plug-ins and components.

This chapter also describes the different components of the SmartCon project. Particularly, it presents the design of the system's main aspects, including the general architecture of the autonomic and the intelligent recommendation system as well as the hybrid and emotional extensions. It also presents examples of some of the mining tasks developed during the project as well as the main characteristics of the developed prototype. More details regarding the methodologies, experiments, and results, etc. have been presented in various works published during this project (Aguilar, Salazar, Velasco, Monsalve-Pulido, & Montoya, 2020; Jimenez, Aguilar, Monsalve-Pulido & Montoya, 2020; Monsalve-Pulido, Aguilar, Montoya, & Salazar, 2020; Salazar, Montoya & Aguilar, n.d.; Salazar, Aguilar, Monsalve-Pulido, & Montoya, 2020; Salazar, Aguilar, Monsalve-Pulido & Montoya, n.d.; Varela, Aguilar, Monsalve-Pulido & Montoya, n.d.-a,b). An additional goal of this chapter is to present all of these works and show how they are coherently integrated.

The remainder of this chapter is organized as follows. Section 2 describes the related works with SmartCon and the domains that are covered by this project, while Section 3 presents the evolution of the architecture for SmartCon. Section 4 describes the various mining tasks conducted during the project in order to extract knowledge for the recommendation system, while Section 5 explains the proof of concept or the prototype of SmartCon as well as some actual courses that employed this prototype. Finally, Section 6 presents the main contributions, conclusion, and future recommendations.

Related Works

Recommender systems have been widely studied in the literature, due to their vast array of applications. In fact, there are many applications for the recommendation of products, movies, news, academic resources, etc. (Adomavicius & Tuzhilin, 2005). In the literature, recommender systems have been classified into four main categories, according to how the recommendation is made: 1) content-based recommendations (CB); 2) collaborative filter recommendations (CF); 3) intelligent recommendations; and 4) hybrid recommendations (Balabanovic & Shoham, 1997). In previous research (Aguilar, Valdiviezo-Díaz, & Riofrio, 2017), the authors developed a general framework for an intelligent recommendation system integrating the processes of learning, inference, etc. This system consisted of the following components: knowledge modeling, learning methods, and reasoning mechanisms.

According to Shardanand & Maes (1995), the systems that perform content-based recommendations include some limitations. For example, they are not very efficient at recognizing the differences between two items of diverse qualities, even if the items include a large number of words in common. This makes these systems somewhat poor at evaluating item quality, since they significantly depend on users' perceptions. Additionally, Shardanand & Maes confirmed that it is not easy to find items that are apparently not of interest to users, but are actually good enough to be recommended. These types of problems are not frequent in collaborative filtering systems, since they are not based on the contents of the items, but on other users' opinions about the recommended item (Cacheda, Carneiro, Fernández, & Formoso, 2011). In this regard, a user's profile is based on the ratings given to the items. This feature also allows the system to be able to recommend items without analyzing their contents, thus making it useful to recommend any type of element. An example of this can be found in the cases of Ringo (Shardanand & Maes, 1995) and Video Recommender (Hill, Stead, Rosenstein, & Furnas, 1995), which are e-mail and web-based systems for recommending music and movies, respectively.

As for the recommendation systems based on collaborative filtering, they also present problems such as scalability, complexity of their models, sensitivity to data changes (Cacheda et al., 2011), sparsity of the rating matrix (Huang, Chen, & Zeng, 2004; Sarwar, Karypis, Konstan, & Reidl, 2001), cold start (Schein, Popescul, Ungar, & Pennock, 2002), shilling (Chirita, Nejdl, & Zamfir, 2005; Lam & Riedl, 2004), etc. Due to these issues, many recommending systems use a hybrid approach that mixes content-based and collaborative filtering methods. In particular, this can minimize the problems that occur when they utilize a single approach. Examples of hybrid recommender systems exist in the academic world because the aim is to personalize the teaching-learning process. A general architecture for a hybrid recommendation system, which uses effort-based learning to improve quality over time, is proposed in Golovin & Rahm (2004). In the application of the recommendation algorithms, the authors included context variables such as content, user, and time. Another proposal of a hybrid architecture, which recommends open courses and educational resources, is presented in Vladoiu, Constantinescu, & Moise (2013). This architecture created a combination of two types of recommendations: one based on enhanced cases (guided by a quality model), and another based on user feedback (collaborative).

In addition, an interesting example of a recommendation system architecture in the academic arena is the one proposed in Zhu, Ip, Fok, & Cao (2008), where a recommendation methodology based on multiple hierarchical intelligent agents is presented. This methodology performed static and dynamic modeling of the users, and offered several functions, including the generation and adjustment of learning plans, personalized recommendations, and learning progress assessments in real time.

One of the most important elements in teaching-learning processes is the construction of knowledge based on collaboration. For example, in Knob, Esteves, Granville, & Tarouco (2017), a multi-agent, client-server application architecture is proposed to recommend different types of activities. More specifically, this architecture considers the set of functionalities in the application and the operations necessary to access them for the exchange of knowledge in virtual communities. Such functionalities are then used by the personal agents in Android, who execute their tasks while achieving their individual and collective objectives. This proposed architecture has been mainly used in the context of smart cities, helping them achieve the objectives of decentralization for the management of communities.

Moreover, educational systems can take advantage of the emotional state of students to enhance their learning processes, as evidenced by numerous investigations. Some studies have even built emotional-aware learning systems, and compared their performance to non-emotional-aware learning systems in order to observe any improvements in students' academic performance (Faria et al., 2017; Pekrun, 1992; Shen, Wang, & Shen, 2009).

Other authors have analyzed the correlation between emotional features and the evaluations of students, thus highlighting the relationship between emotions and learning performance (Chauhan, Agrawal, & Meena, 2019; Immordino-Yang & Damasio, 2007; Yu et al., 2018).

In a related study, Shen et al. (2009) found a 91% increase in e-learning performance by using emotional data. This increase was especially observed in user-centered learning. They also noted the lack of research in detecting emotions during the learning process in real time. Meanwhile, Pekrun, Goetz, Titz, & Perry (2002) and Yu et al. (2018) noted that positive emotions can promote self-regulation among students, whereas negative emotions can lead to dependence on external orientation. In general, these studies assume that not all emotions are relevant to learning, but only a small subset of them, with different investigations proposing several emotions related to learning. For example, Shen et al. (2009) focused on four emotions and observed a 91% increase in e-learning performance by only analyzing this subset of emotions, compared to a system with no emotion analysis. It is also important to consider that the type of education (e.g., self-learning, classroom lectures, group discussions, etc.) implies non-identical processes and requires different considerations.

Finally, several works have proposed intelligent recommender systems, some of them in the e-learning domain. For instance, Tarus, Niu, & Mustafa (2018) reviewed literature on ontology-based recommenders for e-learning. They also categorized the different recommendation techniques used in ontology-based, e-learning recommenders, according to the knowledge representation technique, ontology type, and ontology representation language in ontology-based recommender systems, in addition to the types of learning resources recommended by e-learning recommenders. Obeid, Lahoud, El Khoury, & Champin (2018) presented an approach for developing an ontology-based recommender system, with improved machine learning techniques, to orient higher education students. The main objective of their ontology-based recommender system was to identify students' requirements, vocational strengths and weaknesses, interests, preferences, and capabilities to recommend the appropriate major and university for each one. Finally, Vijayakumar, Vairavasundaram, Logesh, & Sivapathi (2019) presented a new travel recommendation system employed on a mobile device that generates personalized travel planning, including multiple points of interest (POIs). This personalized list of recommended travel destinations was based on a heat map of previously visited and highly relevant POIs.

Architecture

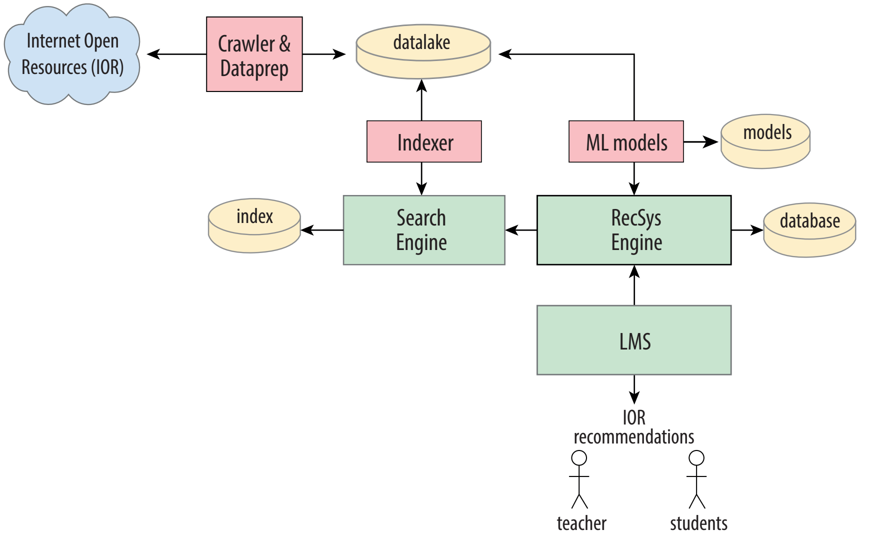
This section presents the architecture of the recommendation system for virtual learning environments (VLEs) proposed by Monsalve-Pulido et al. (2020). This architecture includes four sections, beginning with a general overview of the architecture, followed by a specific description of the autonomous recommendation system. Next, the hybrid recommendation component is presented in detail, after which its extension as an affective recommendation system is described.

General Architecture

SmartCon is a project that harvests millions of free and open digital resources on the Internet or "Internet Open Resources" (IORs), which are stored in a data lake for further processing. In the harvesting stage, the sources, crawling, and processing of the raw data are identified in a normalized manner. Next, the data is processed through a search engine and a machine learning (ML) processor, after which it is used as an indexer and for ML techniques. In this case, the search engine is an implementation of the first version of the recommendation system, which is based on the data contents (i.e., the RecSys).

Overall, the ML processor follows three objectives: 1) to process the data and enrich the metadata indexed in the search engine; 2) to generate new data and models to improve the precision of the recommendations; and 3) to implement new features, such as clustering, top-n-related data, and collaborative filtering, incorporated into the RecSys Version 2 (i.e., smart and collaborative filtering RecSys). Meanwhile, the RecSys engine performs three tasks: 1) it pre-calculates a recommendation for each course-student pair; 2) it receives the requests from the LMS and returns the recommendations; and 3) it processes logs, favorites, students, and course profiles. Finally, the LMS is a learning environment in which students and teachers access courses, including contents and activities, and receive recommendations from SmartCon. Figure 1 presents the general architecture of SmartCon.

Figure 1. The General Architecture of SmartCon

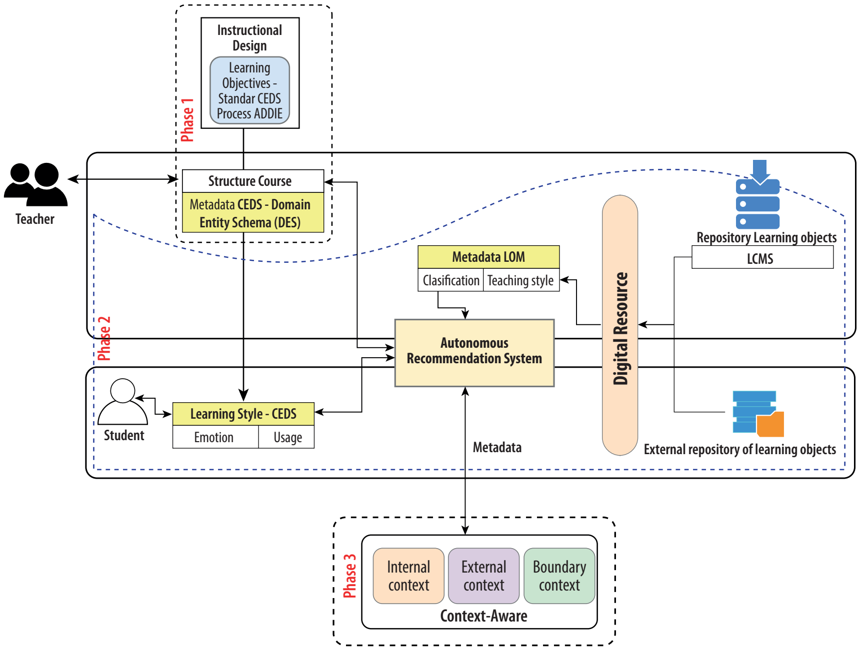


Source: Prepared by the authors

Autonomous Recommendation System Architecture

This section presents the architecture of the autonomous recommendation system (ARS) proposed by Monsalve-Pulido et al. (2020). This architecture is based on two general principles. The first is autonomous computing using a self-managed computing approach, while the second is an intelligent recommendation system (Aguilar et al., 2017). Figure 2 describes the architecture of the ARS for teaching-learning processes in VLEs. Overall, the architecture is composed of three general phases: 1) the creation of academic courses; 2) the utilization of digital resources by students; and 3) the extraction of all of the necessary context variables in order for the architecture to recommend academic contents to students and teachers.

Figure 2. Architecture of the ARS



Source: Prepared by the authors

Table 1 describes the objective of each phase of the architecture as well as the metadata used.

Table 1. Phases of Architecture

Phase	Objectives	Metadata
Phase 1	Creation of the academic course structure and instructional design.	ADxuation (Kruse, 2002) Common Education Data Standard (CEDS) (NCES, 2014)
Phase 2	Extraction of student information (e.g., academic information–learning styles) and information from academic digital resources (e.g., internal and external repositories).	Learning Object Metadata (LOM) (of the IEEE P1484.12.2/D1, 2002). Common Education Data Standard (CEDS) (Kruse, 2002)

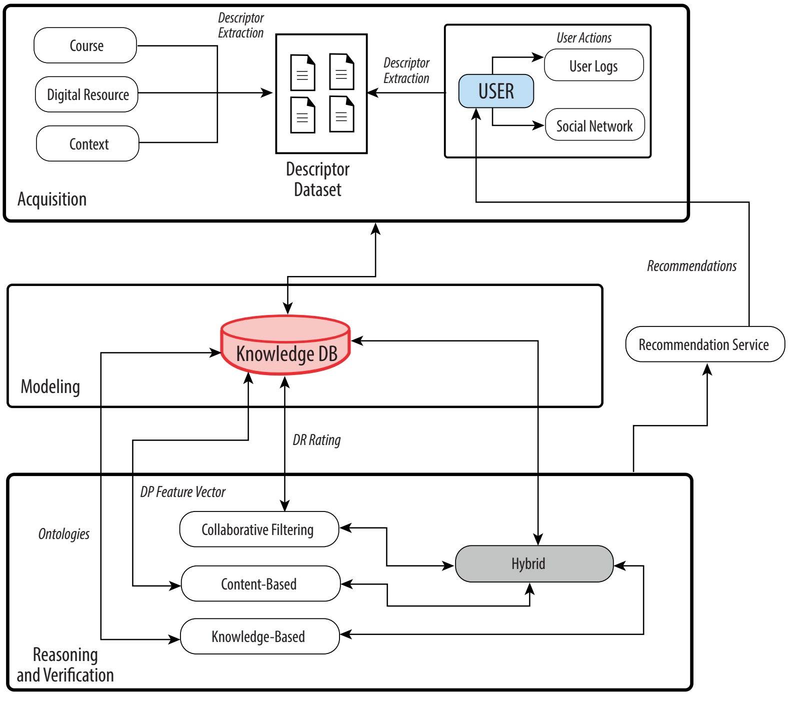
Phase 3	Extraction of context variables (e.g., internal, external and border) for the personalization of learning.	Learning Object Metadata (LOM) (of the IEEE P1484.12.2/D1, 2002). Common Education Data Standard (CEDS) (Kruse, 2002) Social networks Global Positioning System, others.

Source: Prepared by the authors

Intelligent Dimension

The ARS is defined by the intelligent dimension shown in Figure 3, which is composed of knowledge representation, learning methods, and reasoning mechanisms. Thus, the intelligent dimension of the ARS includes three main layers: 1) acquisition; 2) modeling; and 3) reasoning and verification.

Figure 3. Architecture of the Intelligent Dimension



Source: Prepared by the authors

Acquisition: In this layer, the information is extracted from two general areas. The first one is the student information generated in the teaching-learning process, which includes identifying the learning styles and all of the contextual information registered in the VLEs, social networks, connection logs, etc. The second one is the academic content, which includes extracting the information through the metadata of the educational process, including academic digital resources (e.g., books, scientific articles, learning objects, patents, etc.).

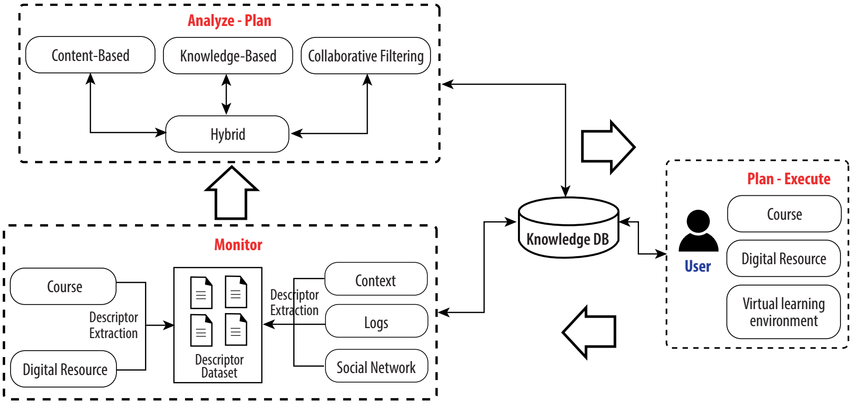
Modeling: The modeling layer stores the information from the results of the acquisition and reasoning and verification layers in a knowledge database. It begins with structured storage based on the metadata of digital resources, academic courses, students, and contexts that interact in the acquisition layer. Moreover, the recommendation results are stored in this layer by means of classification vectors, while the ontology results are from the reasoning and verification layer.

Reasoning and verification: The main objective of this layer is to effectively recommend digital academic content to teachers and students. Different reasoning mechanisms can be used in this layer (e.g., deductive, inductive or abductive). This recommendation process also uses hybrid recommendation techniques by combining the collaborative filtering, content- and knowledge-based filters.

Autonomous Dimension

The autonomic architecture of the recommendation system aims to guarantee self-management and adaptability in any context, without human intervention. In order to meet the autonomic objective, the Monitor-Analyze-Plan-Execute-Knowledge (MAPE-K) model (Vizcarrondo, Aguilar, Exposito, & Subias, 2017) was used, as described in Figure 4.

Figure 4. Architecture of the Autonomous Dimension



Source: Prepared by the authors

In Table 2, the components of the autonomous dimension are described by means of the iterative processes of the MAPE-K model.

Table 2. Components of the Autonomic Dimension

MAPE-K	Objective	Knowledge DB
Monitor	Extract the properties of the digital resources, academic courses, and context information.	Store-consult
Analysis–Planning	Process the information from the monitor stage. Run the hybrid recommendation filter.	Store and query results to estimate future recommendations
Planning–Execution	Deploy recommendations on the virtual learning platform, according to the needs of teachers and students.	Store-consult

Source: Prepared by the authors

Generic Hybrid Adaptive Architecture

Various techniques have been proposed for recommending items to users in different contexts and domains. They are mainly classified into four approaches: 1) content-based (CB); 2) collaborative filtering (CF); 3) knowledge-based; and 4) hybrid. However, many others have emerged with the vast amount and variety of available data.

CB algorithms recommend items that match the user's preferences or profile, which is mainly defined by the items that the user has previously chosen. They also use keywords, tags or weights to characterize the objects. For example, the TF-IDF representation is a frequently used tool to obtain certain features (Aguilar et al., 2017; Burke, 2007).

CF approaches are based on the user's behavior and rating patterns in relation to other users. In general, collaborative techniques can be either memory- or model-based. The first one uses the concept of neighborhood to find similar users (or items), while the second type is derived from historical data to make predictions (Burke, 2002, 2007).

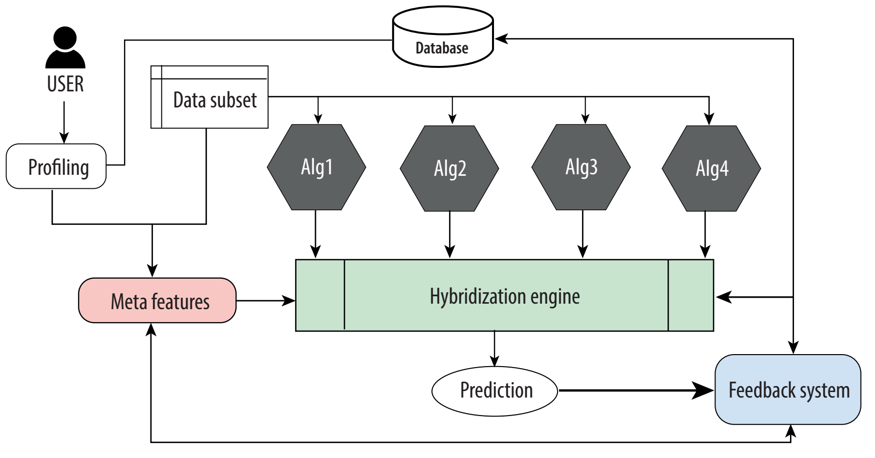
Given the strengths and weaknesses of each technique, such as the cold start problem when there is a lack of data, hybrid approaches have been widely used to improve performance by combining different types of recommendation algorithms, also known as "hybridization methods." There are many ways in which they can be combined, most of which are presented as follows (Burke, 2002, 2007).

- Weighted: The scores are numerically combined.
- Switching: The components are turned off and on, according to certain criteria.
- Mixed: The output from different recommenders are presented together.
- Feature combination: The features from different sources are combined into a single algorithm.
- Cascade: The output from one technique is used as an input feature for another.
- Meta-level: The model learned by one algorithm is used as the input for another.

Despite the improved performance over single algorithms, hybrids also present certain challenges, especially when they are implemented in actual scenarios. It is well known that data varies over time and that there is no static configuration that will optimally work for all recommendation requests. Thus, the adaptability of the system has been garnering interest, particularly as more data are emerging and more digital environments are requiring this type of service.

In Figure 5, a generic adaptive hybrid architecture is proposed, which follows the dynamic behavior of the environment through the use of metrics (i.e., meta-characteristics), from which the hybrid configuration for the recommendation is determined.

Figure 5. Generic Hybrid Adaptive Architecture



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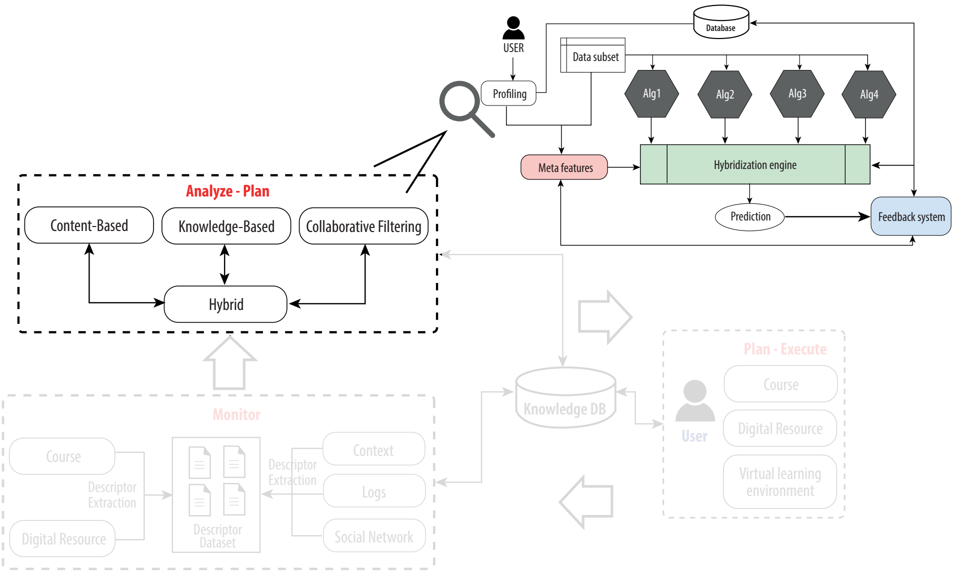
As shown in this figure, the architecture can adapt to different domains. In our case, the users would be students in a VLE. When a student enters the system for the first time, he/she completes a survey with their preferences, after which the system reduces the universe of interest for the student, since computing the subsequent processes with a large number of documents would be inefficient.

In general, the algorithms that are combined in hybrid systems should be of different types in order to take advantage of their characteristics and compensate for their weaknesses. The red block, identified as "meta-features", is a key component in this system that represents a set of numerical indicators used to describe the users (or items) at a specific moment. The idea is that the high or low values of these dynamic variables reflect multiple characteristics of the context, which can be used to configure the hybrid blend in a more optimal manner.

Meanwhile, the feedback engine is responsible for capturing the logs and other variables that allow the system to perform different tasks such as checking the usefulness of the recommendations (and potentially optimizing them), recalculating the meta-features to update the context status, and enriching the data inputs for the algorithms (mainly the collaborative-based ones).

The generic hybrid adaptive architecture is incorporated into the autonomous recommendation architecture, as shown in Figure 6.

Figure 6. Incorporation of the Generic Hybrid Adaptive Architecture into the ARS



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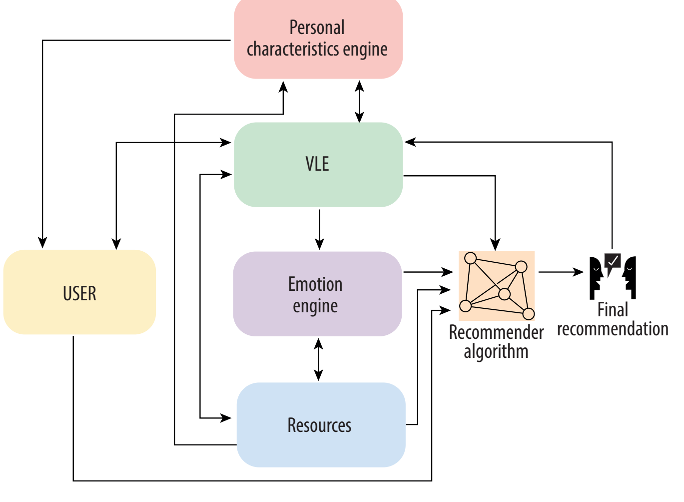
The incorporation of this component into the ARS is achieved through the MAPE-K model. More specifically, it occurs in the "Analysis–Planning" phase, in which it executes the hybrid recommendation filter (i.e., collaborative filter, based on content and knowledge), thus defining the correct combination for guaranteeing high-quality content recommendations (see Varela et al., (2020a,b) for more details).

Generic Architecture of an Affective Recommender System for e-learning Environments

The proposed architecture for an affective recommender system is presented in Figure 7. It consists of five major components: 1) user; 2) personal characteristic engine; 3) VLE; 4) emotion engine; and 5) resources. Briefly, the user component stores all of the information regarding the user's profile, while the personal characteristic engine extracts personal characteristics from the user such as personality traits and learning style. Moreover, the VLE component is the e-learning environment of the user, while the emotion engine captures (but does not store) the emotional information of the user and the course contents (i.e., the learning resources). Moreover, the resources component stores the metadata of the learning resources and the emotional logs of the user when interacting with the contents (see Salazar, Montoya & Aguilar (n.d.) for more details).

Figure 7. Generic Architecture of an Affective Recommender System



Source: Prepared by the authors

The proposed flow is as follows. A student enters the VLE and registers him/herself. During the registration process, personal information is captured, and questionnaires regarding personal traits and learning styles are completed. Additionally, the expertise level of the student can be obtained by using quizzes or questionnaires during registration. In this case, such processes are executed by the personal characteristics engine. All of this information is then stored in the user's profile, except for the expertise level, which is stored in the VLE database.

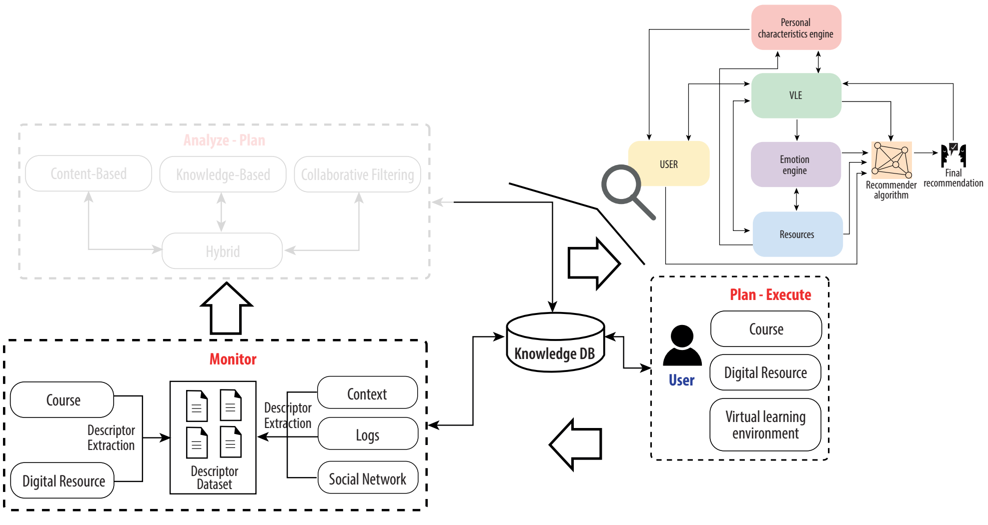
When a student is registered, he/she can log in on the platform and interact with the different contents. While the student is using the contents, several logs are captured by the VLE logger and stored in the VLE database. Meanwhile, the emotion engine captures the students' emotional information before, during, and after using the contents through multiple sources such as a camera, microphone, questionnaires, etc. Such sources are low-invasive and unobtrusive when obtaining such information during the learning process. The collected emotional information is then stored in the Resources module, in a special database. This information not only includes the emotions felt by the student in a specific course, but also some metadata of his/her interactions (e.g., timestamps).

The emotion engine is also in charge of extracting emotional information from the contents, and assigning such aspects, emotional tags/values that can be used for the recommender algorithm. Moreover, the Resources module is in control of storing all of the resource information, including the aforementioned emotional tags/values and the emotional logs from the student using the resources. Since learning styles, expertise levels, and (in some cases) personality traits are dynamic, the personal characteristic engine periodically implicitly assesses these characteristics through logs or explicitly administers questionnaires to the student in the VLE.

Finally, the recommender algorithm collects the information from the user's profile, VLE logs, emotional logs when interacting with the resources, his/her current emotional state, and the metadata of the resources in order to generate personalized content recommendations. The recommendation logs are then stored in the VLE for analyzing the performance of the recommendations, and boosting the recommender algorithm.

The generic hybrid adaptive architecture is incorporated into the autonomous recommendation architecture, as shown in Figure 8.

Figure 8. Visualization of the Emotional Architecture in the ARS



Source: Prepared by the authors

The incorporation of this component into the ARS is carried out through the MAPE-K model, specifically in the "Monitor" and "Plan–Execute" phases. In this case, the "Monitor" phase recognizes the emotions of the student, while the "Plan–Execute" phase executes the emotional recommendation filter to exploit this source of information, and to guarantee high-quality content recommendations.

Mining Tasks

Content Analysis

Content Feature Extraction

The classification of the contents was performed according to topics and keywords, using the Latent Dirichlet Allocation (LDA) technique. This topic generative model is widely used in natural language processing (NLP) for topic modeling and other tasks. It also generates K topics (K, as a tunable parameter) from the documents in a corpus (i.e., a collection of documents), and estimates two distributions: 1) the distribution of topics in a document; and 2) the distribution of terms in a topic. In addition, this technique not only treats documents in regard to their relevance to the topic, but it also extracts two types of metadata from the contents: 1) keywords; and 2) descriptors of textual data. Moreover, the LDA technique gives a percentage regarding the membership of a document to a topic, i.e., the document is assigned to the topic with a higher percentage.

On the other hand, keywords were assigned as follows. They were extracted from the topic to which each document belonged (to a greater extent), taking the top p as more relevant in terms of the topic. In other words, for each document, the LDA technique assigned a set of K membership percentages of the specific document to each topic, after which the topic to which the document belonged the most was selected. This technique also gave a set of m (m = number of different terms in the corpus) relevance of each term to each topic. The top p relevant terms in the previously selected topic were then chosen as the keywords of the specific document. In our experimentation, p was set to 5.

Finally, two types of metadata were used for enhancing the generated recommendations. The keywords were then added to the information retrieval system. The intention was to generate keywords for all of the documents in order to generate better recommendations (see Aguilar et al. (2020) for more details).

Content Grouping

Content grouping was performed utilizing the textual descriptors (extracted with the LDA technique) to calculate similarities and generate recommendations. For extracting the textual descriptors, the set of memberships of each document to each topic was selected, thus obtaining a K-dimensional vector for each document and indicating the percentage of the membership of the document to each K topic. These vectors were primarily composed of low membership percentages, with only a few topics, presenting a considerable percentage for each document.

Moreover, the vectors representing the textual data of the documents were used to calculate similarities between them. This was helpful for providing pre-calculated recommendations for the students. For example, when a student rates the content as relevant, he/she may be interested in similar contents for learning. Thus, with the vector of a document, the cosine similarity was used for calculating the top *p* most similar contents and recommending them to the student that rated the document as relevant (see Aguilar et al. (2020) for more details).

Audio Feature Extraction

In general, many academic resources found on the Internet are multimodal objects (e.g., texts, audio, images, video). Thus, it was necessary to have efficient methodologies for extracting the descriptors that allow the resources to be characterized and recommended to the students and teachers in an appropriate manner.

Traditionally, the extraction of audio descriptors consists of extracting the text content from the audio, and then performing text mining. However, there is a significant amount of audio (i.e., non-text) information contained in many learning resources (e.g., video tutorials) that is not exploited, including frequency (in Hz), loudness or sound intensity (in decibels), reverb (in sec), etc. In some cases, the audio data does not include speech. As a result, no extraction of text content is possible.

In this project, an automatic feature engineering methodology was proposed for the audio data, which can automatically extract, analyze, and select the best features for such data (Jimenez et al., 2020). In this case, different types of characteristics in the audio data were considered such as sound engineering, basic statistics, and the time-series domain. In regard to the latter, each audio sample was considered as a time-series set, since the set of variables was measured at different times, and each variable (i.e., the time-series) was characterized by a set of time-series descriptors. The proposed approach can also be developed in different ways, since various methods of exploring combinations of characteristics (e.g., genetic algorithms) and different types of evaluation functions can be used to select the characteristics, with some based on grouping or classification metrics, and others based on information theory (see Jimenez et al. (2020) for more details).

Emotion Recognition

For recognizing the emotions of the students, three sources of information (i.e., modalities), which were non-invasive or obtrusive, were used: 1) the audio from the student's speech was captured by a microphone;

2) the facial expressions were captured by a camera; and 3) the text was obtained from student's interactions such as the reviews of the contents and related chats. As for the emotion recognition process, it was performed in two phases: unimodal and multi-modal. In the first phase, the data was analyzed separately from each modality in order to obtain the recognition by each modality, while the second phase consisted of fusing the decisions from the modalities to obtain a more robust final recognition. These steps are described in the following sub-sections (see Salazar et al. (2020, n.d.) for more details).

Unimodal Phase

In this project, each modality was separately processed in the following order: 1) feature extraction; 2) feature selection; and 3) recognition. For the audio modality, 6,373 features (INTERSPEECH 2013 COMPARE feature set (Schuller et al., 2013)) were extracted from each audio sample. For the video modality, 68 facial landmarks were extracted, after which the distances between each landmark (normalized by the height of the face detected) was used as the feature for each image. Meanwhile, in order to summarize the frames in a video, the average of the frames' features in the video was used, resulting in a total of 2,278 features per video.

As for the texts, two knowledge bases were used for extracting the affective information from each word: Senticnet 5 (Cambria, Poria, Hazarika, & Kwok, 2018) and AffectiveSpace (Cambria, Fu, Bisio, & Poria, 2015). From Senticnet 5, seven features were extracted from each word, i.e., five continuous and two categorical. From AffectiveSpace, 100 continuous features were extracted for each word. Moreover, for the text, 105 continuous and two categorical features were extracted. In order to summarize the features of words in a text, the percentiles 0, 25, 50, 75, and 100 were used for continuous variables, while the summation of categories was used for each categorical feature, resulting in 441 features (i.e., 105 continuous * five percentiles + two categorical * eight classes).

When all of these features were extracted, the relevant ones were selected in the following three ways (i.e., filters): 1) removing the features with a variance lower than $1 * 10^{-4}$; 2) avoiding multicollinearity by only keeping the features with a variance inflation factor (VIF) lower than 10; and 3) conserving the characteristics with a relevance greater than

$1 * 10^{-3}$. This relevance was calculated by using a random forest model and utilizing the information it provided about the importance of the variables. At the end of the feature selection process, 131 aural, 21 facial, and 224 textual features were selected. In addition, unimodal models were constructed for each modality, with the ML techniques including support vector machines (SVM), random forest, and partial least squares (PLS) regression. Overall, PLS regression provided the best results for each modality in terms of R2 and relative error of standard deviation.

Multi-modal phase

This phase fused the features or recognitions obtained from each modality in the previous phase, and generated final robust recognition results by using the information from the three modalities. In virtual education, students are, in general, not writing or talking all of the time. Thus, audio and textual data are only available at certain moments. For this reason, the multi-modal fusion model must deal with the missing data (i.e., the missing modalities).

Overall, three approaches were proposed and compared, with two based on decision-level fusion and one based on feature-level fusion. The first approach concatenated the recognition from each modality and filled in the missing modalities with zeros, obtaining a six-dimensional vector as the input for the model. The second approach used recurrent neural networks, which varied the input length and dealt with the missing modalities. Finally, the third approach was very similar to the first, but it concatenated the extracted features and filled in the missing modalities with zeros. Moreover, the models used for the three approaches were different light architectures of neural networks, due to the possible scalability issues a VLE could face.

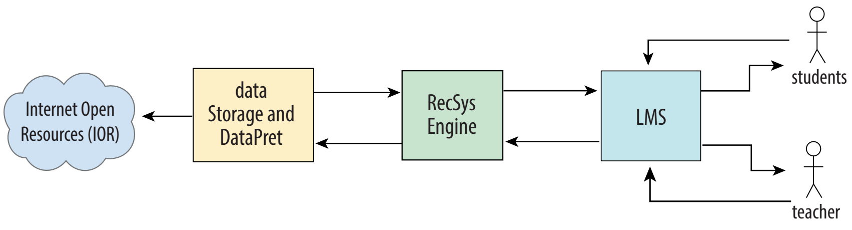
Pilot Testing

This section introduces the technological development process of SmartCon. It also describes the use of SmartCon in the hybrid and virtual courses at EAFIT University.

Design, Development, and Implementation

SmartCon is a system composed of several reference architectures that integrate big data, data analytics, artificial intelligence, and software development technologies into one product. The general architecture of SmartCon is defined by three main modules, as shown in Figure 9.

Figure 9. General Architecture of SmartCon



Source: Prepared by the authors

- *IORs:* The Internet includes many digital resources that can be used to help various learning activities. However, the main issue is how teachers or students can find appropriate content among the millions of resources. Thus, the first step is to identify the main resources on the Internet.
- *Data Storage and Data Prep:* All of the resources are collected into a data lake using different types of robots and crawlers. The documents and resources are then pre-processed to standardize and facilitate their further utilization in the data mining tasks.
- *RecSys:* This module is based on two components: 1) a search engine; and 2) an application that implements a recommendation system founded on the content-based, collaborative filtering, and hybrid methods. The RecSys represents the core of SmartCon because it integrates the different models of analytics, ML, and artificial intelligence. In addition, it not only offers several web services to the LMS in order to send recommendations to the

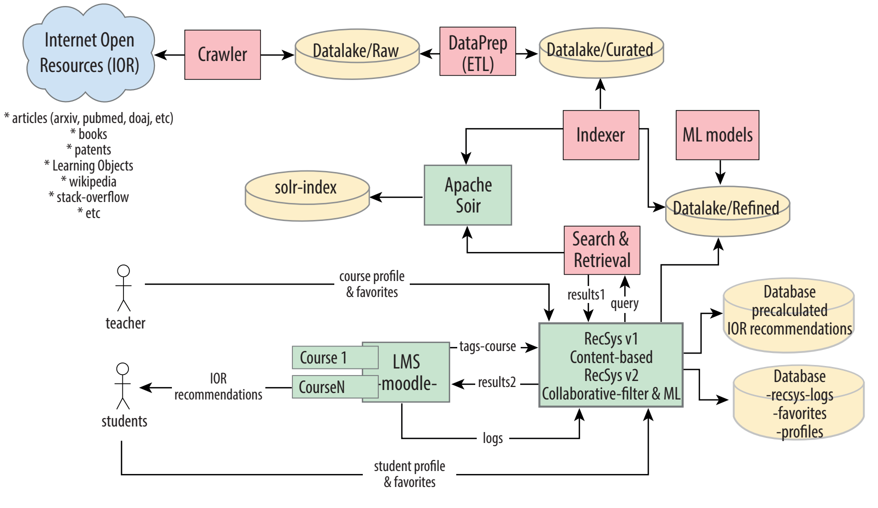
courses, teachers, and students, but it also exposes web services to manage other features, such as profiles, favorites, caches, logs, etc., which will improve future recommendations.

- *LMS:* This is an application in which courses are managed, teachers perform instructional design, contents are loaded, and students interact with such aspects. In order to integrate this LMS in SmartCon, some plug-ins and adapters were developed. Moreover, the LMS received the recommendations from the RecSys module, and it managed several features that improved the recommendations through the learning process.

SmartCon Detailed Architecture

Based on the architecture described in Figure 9, SmartCon defines the components presented in Figure 10:

Figure 10. A Detailed Architecture of SmartCon



Source: Prepared by the authors

- *IORs:* SmartCon identifies different categories and sources, which are described in Table 3. These digital resources are mainly texts in different formats (e.g., PDF, HTML, TXT, etc.), characterized as unstructured or semi-structured. Nevertheless, SmartCon also considers the resources from audio, video or other formats.

Table 3. Categories of Digital Resources

Category	Source (MD: Metadata & FT: full-text)
Articles	* Arxiv (MD & FT) * Pubmed (MD) * DOAJ (MD) * OpenAire (MD)
Patents	* WIPO (MD) * USPTA (MD)
Books	* BOAJ (MD)
Wikis	* Wikipedia-English (FT) * Wikipedia-Spanish (FT)
Communities	* Stack-overflow (FT)
Learning Objects	* Merlot (MD)

Source: Prepared by the authors

- *Harvester:* SmartCon collects near 30 million digital resources among the full-texts and metadata. All of the data is stored in a data lake (i.e., the raw zone), after which it is processed by the Data Prep-ETL module. After all of the data is curated, it is stored back in a data lake (i.e., the curated zone), and then it is ready to be indexed and analyzed by ML techniques. The main purpose of the Data Prep module is to filter some fields by source and place all of the documents in the same format in order to facilitate further processing (i.e., indexing and data mining).
- *Indexer:* The Indexer places the normalized IORs into a search engine. In this project, we used Apache Solr. This search engine supported the first version of the recommendation system, which was content-based using an information retrieval system.
- *ML Models:* The core of SmartCon is that the models are implemented using ML techniques. In the ML stage, we designed and implemented several ML models (supervised and unsupervised). These models focused on improving the metadata to be indexed into the search engine, and generated new data to support the RecSys.

- *Search Engine:* SmartCon uses an information retrieval system based on Apache Solr, which is a popular open-source software to index, search, and retrieve multiple types of files. Apache Solr is based on Apache Lucene. Thus, it supports full-text data (PDF, HTML, JSON, CSV, DOC, etc.), which includes the data sources in SmartCon. The standard file format indexed by Apache Solr is CSV.
- *Recommendation System (RecSys) Engine:* SmartCon uses two types of RecSys: content-based and collaborative filtering. Content-based RecSys (based on Apache Solr) is a search engine that retrieves relevant documents, according to certain keywords or tags specified by the teacher in the course's sections and by the students in their personal preferences in the LMS. In this case, the RecSys functions as a traditional search engine, but it is smarter, since the students are unaware of how the documents are selected and organized according to their contexts, profiles, and behaviors. As for collaborative filtering, it is based on ML. More specifically, this RecSys merges several approaches such as hybrid RecSys, collaborative filtering through the use of the RecSys, and the logs from the LMS (Moodle). The main drawback of recommendation systems based on collaborative filtering is the cold start. In order to solve this problem, the RecSys collects various data from the LMS, including logs related to the contents accessed by the students (either from the course or from SmartCon), interactions among the students, etc.
- *LMS:* Finally, the most important module of the architecture is the LMS, in which teachers and students interact and receive recommendations from SmartCon. Within the LMS, teachers can define the course profiles (e.g., tags per course and sections, categories and sources of interest, language, etc.), and manage favorite contents suggested by SmartCon (e.g., contents found on SmartCon or external links), while students can define their own profiles (e.g., categories, sources, language, favorites, etc.). This module is also implemented by using an open-source platform called "Moodle", which is a state-of-the-art LMS from the free-software environment. Additionally, Moodle interacts with SmartCon in

four ways: 1) through plug-ins and blocks developed within SmartCon; 2) by activating the modules of the course and student profiles; 3) by accessing the graphical user interface (GUI) of SmartCon to search for a specific course or student; and 4) by exposing some web services to send logs and information toward RecSys. Moreover, SmartCon can support any legacy or new Moodle.

Big Data Architecture

SmartCon includes the characteristics related to the "5Vs" of big data: 1) Volume: the ability to store high volumes of data (gigabytes to petabytes, due to the large amount of resources available on the Internet); 2) Variety: the main data source is either unstructured or semi-structured; 3) Velocity: the models that are trained and tested require high-performance computing, with bounded processing times; 4) Value: the ability to extract information and knowledge from the raw data; and 5) Veracity: the ability to perform quality processes (filtering and Data Prep).

In general, big data technologies are used as storage (i.e., configured as a data lake and as SQL/NoSQL databases) and as Apache Spark clusters that allow the processing of large volumes of unstructured and semi-structured data.

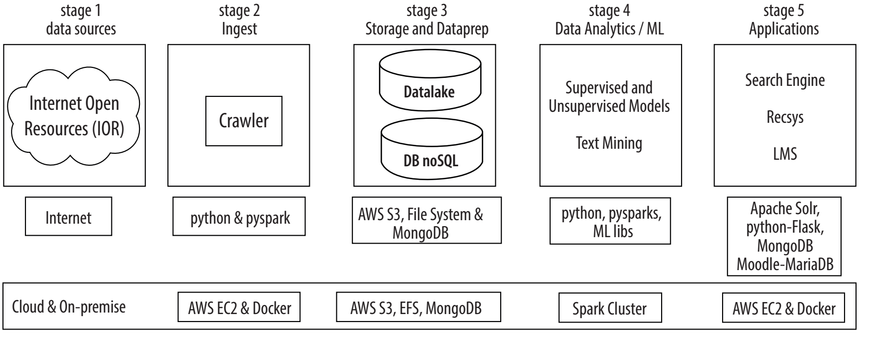
In this project, we used the following five-stage reference architecture:

- Stage 1. Data sources: These include the same sources identified in SmartCon's detailed architecture, mainly based on unstructured and semi-structured data such as text documents, audio or video.
- Stage 2. Ingest: Software robots that collect data from the sources on the Internet.
- Stage 3. Data storage and preparation: The main storage is performed in a data lake, which is designed with four zones: raw, stage, trusted, and refined. More specifically, the data is first stored in the raw zone or in the stage zone if the data requires some pre-processing such as data decompression or file format transformation. Then, a series of extraction, transformation, and loading (ETL) processes are performed, which allow the data to be normalized for later stages of data analysis and the search engine.

- Stage 4. Data analysis: This is considered the main component of the project, since it is the stage of information and knowledge generation toward the intelligent recommendation module. From the perspective of big data, it is the component that allows the execution of ML models over a Spark cluster. The data and output models are stored back in the data lake (i.e., the refined zone) or in NoSQL databases, for later use in the RecSys. This stage primarily runs in a supercomputer environment, with big data clusters based on Apache Spark and Hadoop. In addition, it is mainly deployed in the Academic Data Center at EAFIT University and (to a lesser extent) in the AWS cloud.
- Stage 5. Application: This stage implements the search and retrieval engine modules (based on Apache Solr), and uses the RecSys module for both content and collaborative filtering. It also implements a module for managing preferences, logs, favorites, etc. Finally, it adapts an open-source LMS, such as Moodle, to utilize all plug-ins and adapters. These applications were deployed in the test and the production environment of the pilot test. Moreover, the main deployment was in the AWS cloud, while the testing was conducted at the EAFIT Academic Data Center.

Figure 11 presents SmartCon's big data reference architecture, including the different technologies used and the execution environment:

Figure 11. SmartCon Big Data Architecture



Source: Prepared by the authors

Development and Deployment of SmartCon

SmartCon was implemented through several software components developed within the project. It also used different open-source projects to implement certain components, and employed the research infrastructure at EAFIT University as well as cloud services for project deployment. At the software level, the following modules were developed:

- Crawler: A software module developed in Python and PySpark that runs on a data server and collects all of the data sources on the Internet. The collected data is then stored in a data lake (i.e., the raw zone).
- Data Prep: A software module that runs on a data server and transforms the original data from the Internet into a standardized form in order to facilitate the mining processes and conduct normalization for the indexing module.
- Indexer: A software module that runs on a data server and indexes all of the standardized contents in the search and retrieval engine.
- ML Models: A software module that implements all of the data mining models. It is also a software component that primarily utilizes the big data and data processing infrastructure. It also runs on a Spark cluster, since some models can take hours or even days to run. More specifically, these models mainly run in an on-premise cluster in the Academic Data Center at EAFIT. In this case, the cluster is built using three servers that total 512 GB RAM, 4 TB of SSD storage, 72 cores, and two Nvidia K80 GPUs.
- RecSys: A software module that implements the main core of SmartCon. It integrates the results of the ML models and search engine and exposes a series of web services toward the LMS.

Overall, SmartCon uses the following open-source software:

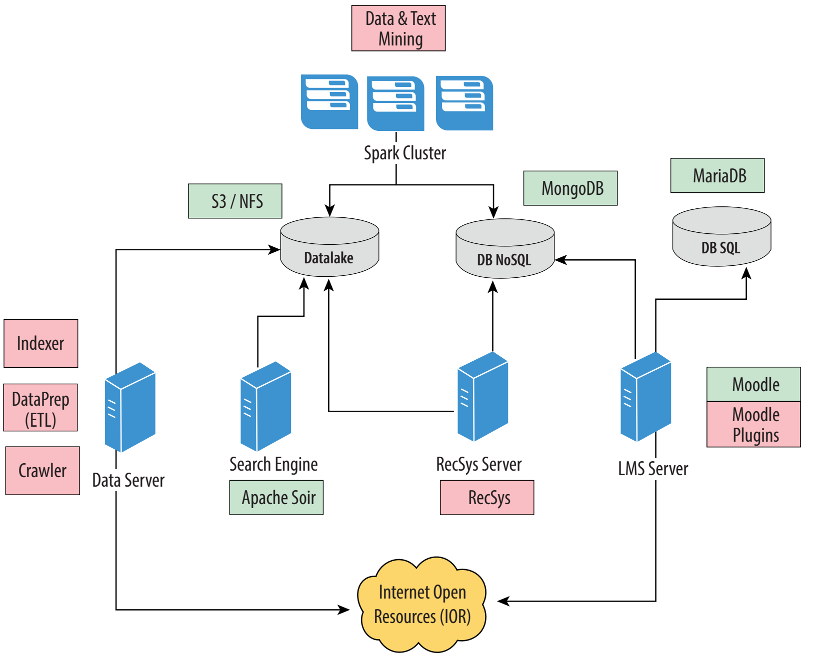
- Apache Solr [1] Version 8.6.2 to implement the search engine.
- NoSQL MongoDB [2] database Version 4.0, in which the RecSys stores the data, logs, student and course profiles, favorites, caches, etc.
- MariaDB[3] SQL database Version 10.3, used by Moodle.

1 https://lucene.apache.org/solr/
2 https://www.mongodb.com/
3 https://mariadb.org/

- LMS Moodle [4] 3.9.2, in which the courses, users (i.e., the students and teachers), contents, etc. are managed. It also creates users for students and teachers, stores course contents, etc.

The deployment and information technology (IT) infrastructure for SmartCon is shown in Figure 12.

Figure 12. Deployment and IT Infrastructure



Source: Prepared by the authors

AWS Cloud Services: At the cloud level, services are primarily used online and in production for the following:

- AWS EC2 virtual machines, which run both native or docker versions of different SmartCon modules. They also run data server, search engine, RecSys, LMS server, DB SQL server, and DB NoSQL server.

[4] https://moodle.org/

- Object storage in AWS S3 to deploy the data lake.
- Load balancers with AWS ELB.
- Name service in AWS Route 53 to manage the domain: contenidosint.org

On-premises servers and Spark cluster: Academic Data Center IT infrastructure, in which the online testing version of SmartCon runs and where they run the following ML models:

- Virtual machines for the testing environment.
- Virtual machines for the software development environment.
- Apache Spark cluster for training and testing of the ML models. This component also runs in batches.

Testing SmartCon

SmartCon has been tested in various courses in the undergraduate computer science program at EAFIT University, including Computational Thinking, Programming Fundamentals, and Special Topics in Telematics.

Each of these courses used the following modules, which were activated in Moodle:

- Recommendation module: The block in which SmartCon recommendations are received.
- Favorite module: The contents that are selected by the teacher, either from SmartCon or external websites. They are also contents from SmartCon that, due to their popularity, are promoted to this category.
- Search module: SmartCon provides teachers and students with a search interface, which can be accessed from Moodle as well as from an external application.
- Profile module: Allows students and teachers to select categories, sources, and language preferences. The objective is to personalize the recommendations generated by SmartCon.
- Scoring module: This module allows the scoring of the contents, both implicitly and explicitly. More specifically, implicitly, it is through a wrapper that intercepts all of the intentions of opening the recommended content, whereas explicitly, it is through ratings such as likes/dislikes or promotions to favorites. All of this data allows SmartCon to "learn" from the interactions with the recommended contents, and to improve its learning algorithms.

- Log module: Allows extracting logs from the Moodle platform to improve the recommendation algorithms, especially the collaborative filtering and hybrid algorithms.

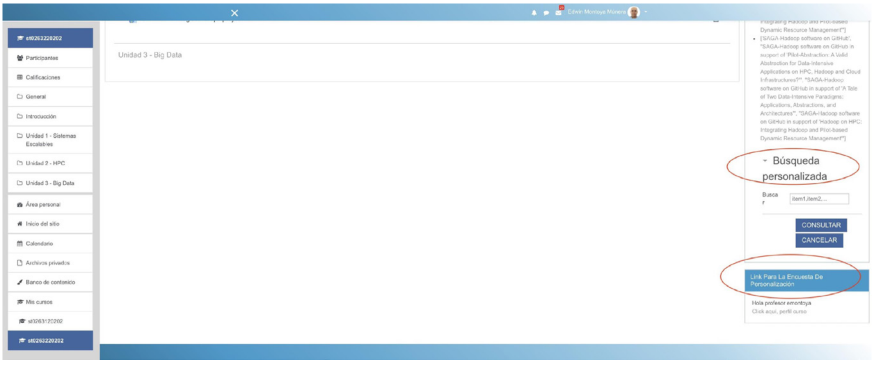
In the GUI Moodle, the following modules are shown. First, the RecSys module is shown in Figure 13.

Figure 13. The RecSys Module

Source: Prepared by the authors

Second, the Search module is shown in Figure 14.

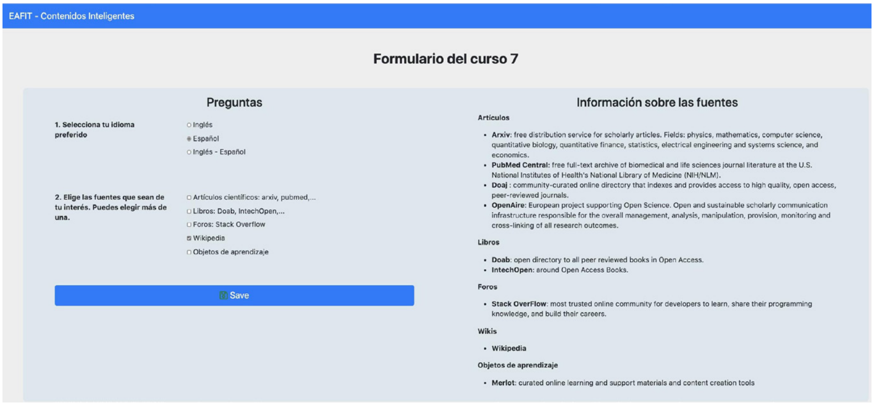
Figure 14. The Search Module



Source: Prepared by the authors

Third, the Profile module is shown in Figure 15.

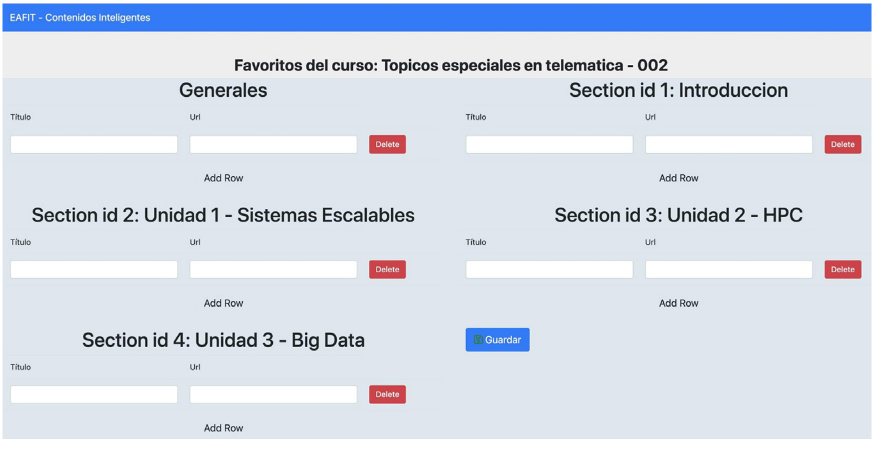
Figure 15. The Profile Module



Source: Prepared by the authors

Finally, the Favorites module is shown in Figure 16.

Figure 16. The Favorites Module



Source: Prepared by the authors

Proposed Testing Methodology

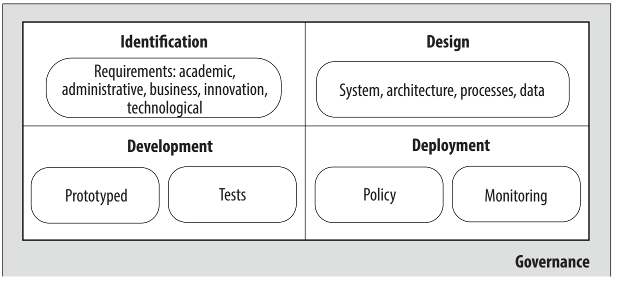
For the recommendation system, the following testing methodology applied in the three aforementioned courses. The methodology consisted of the following three phases:

- *Surveys:* In this phase, three initial surveys were administered to the students. The first was a socio-demographic survey, the second examined learning styles, and the third focused on personalities. As a result of this phase, the data obtained in the Profile module for each student was used to recommend a list of contents for each topic.
- *Content rating:* After recommending such contents, the students rated the list from 1 to 5, according to the level of importance. In this phase, the students mentioned the relevance of the contents, according to the related topic.
- *Evaluation:* Finally, the relevance and precision of the recommended contents were evaluated in order to verify the effectiveness of the recommendation system.

Adapting the ARS Toward a Service-Oriented Architecture (SOA)

The implementation of a SOA architecture will guarantee that the ARS easily adapts to any educational institution's IT. For the implementation of our ARS for VLEs, a SOA methodology, based on Suhardi, Doss, & Yustianto (2015), was proposed, which describes four general phases that guide the construction and management of a service-oriented architecture. The first phase describes the general identification of academic, administrative, business, innovation, technological requirements, etc., while the second phase designs the process, architecture, system, data, and services that can be a part of the architecture. In the third phase, the development and test of each of the previously designed services are carried out, while in the final phase, the architecture is deployed through monitoring, versioning, and the discovery of new services (see Figure 17). Each of these phases can be articulated with SOA governance, in which the processes and activities must be aligned with institutional IT policies.

Figure 17. General Methodology for Adapting the ARS Ioward an SOA



Source: Prepared by the authors

Conclusion

This chapter presented the main contributions of the SmartCon project. The main goal was to integrate different free sources and digital contents from the Internet in order to build an ARS that recommends contents to different users in an educational context, based on big data analytics, autonomic computing, and artificial intelligence paradigms.

Overall, the SmartCon project included five major components: 1) a data lake to store open digital resources; 2) processing tasks to prepare the sources of information; 3) data analytics tasks to enrich the knowledge of the contents, courses, students, and teachers; 4) a search engine system; and 5) a recommendation system to personalize the contents to different users (e.g., students and teachers). In addition, the project developed a prototype called SmartLMS, which is an open-source LMS that uses our recommendation system.

Particularly, the project defined the concept of an ARS (with intelligent and autonomic capabilities) and its extensions to consider hybrid recommendation algorithms and emotion recognition. These aspects are important characteristics that can be easily added to an ARS (according to its MAPE-K model), thus supporting the robustness of the system recommendation process.

Meanwhile, the hybrid recommendation process was adapted to the data at the moment of execution, after which the hybridization was dynamically configured for each user, depending on the advantages/

disadvantages of the various recommendation approaches. In this case, the recommendation approaches were determined in real time (see Salazar et al. (2020, n.d), Salazar, Montoya & Aguilar (n.d.) and Valera et al. (n.d, -a,b) for more details). More specifically, the proposed fuzzy system for managing the integration of the recommendation approaches (using the defined metrics) included the ability to solve existing problems, such as cold start, in the individual recommendation algorithms.

Moreover, the SmartCon project developed different mining tasks for the various tasks required by the ARS. For example, it proposed different content extraction approaches and featured an engineering process for audio datasets. It also analyzed different recognition approaches and meta-features that could be used to guide the hybrid recommendation process.

Finally, the project developed a prototype in which it clearly defined the platform required by our ARS. Particularly, the prototype was composed of a data lake, a ML module, a search engine system, a recommendation system, and a LMS.

As for future recommendations, research must exploit the different sources of knowledge incorporated by our proposal in a smart classroom in order to improve the learning process. In this regard, various concepts, such as autonomous learning analytics cycles (Aguilar, Cordero, & Buendía, 2018) that allow the natural integration of context information in a dynamic process of continuous improvement, should be used. Furthermore, future works should analyze the results of the learning process using appropriate metrics that can measure the overall impact of our recommendation system on students.

Acknowledgments

This work was supported by Project No. 64366 "Contenidos de aprendizaje inteligentes a través del uso de herramientas de Big Data, Analítica Avanzada e IA" –The Ministry of Science –The Government of Antioquia –The Republic of Colombia.

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Omnichannel for Learning

DOI: https://doi.org/10.17230/9789587207002ch2

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Introduction

From an early age, the "digital natives" generation has naturally adapted to electronic devices in their homes, schools, and workplaces by interacting with different environments through computer technologies. Prensky (2001) said that digital natives have adopted parallel habits associated with the development of multiple tasks. For instance, they prefer to receive information graphically and find satisfaction with immediate feedback about their progress.

These characteristics identify individuals who are more likely to access virtual education programs or complementary education courses to increase their professional level. Although virtual learning environments are not a new academic space, computer technologies for virtual or digital education are currently undergoing accelerated use and consequently require innovative development. The massive worldwide incursion of virtual courses, academic platforms, and higher education programs have significantly impacted countries in constant growth, such as Colombia. Today's view of digital transformation is influenced by the accelerated evolution of mobile devices and their technological elements that move world trade and generates a cultural change. This change directly impacts the educational process by generating challenges and establishing new teaching and learning styles.

Recent technological developments in data management and processing, linked to the advancement of countless new digital channels, offer the possibility of managing information and distributing it to different types of users globally. In other words, users can access different services through different channels. The services they access meet the needs, requirements, and particularities to guide the micro-segmentation and personalization of supply and demand. Notably, personalization is possible due to information technologies that have had their best expression in marketing. Micro-segmentation is individualized to understand and recognize behavior patterns, preferences, purchasing power, needs, aspirations, and other variables to offer users tailormade products and services. Many information technologies, data, and capacities are joined together to sell better, in greater quantity, and with greater efficiency and impact. Which brings forth the question: Why not use the same marketing strategies to educate better with more coverage and greater efficiency and impact?

This chapter presents the research results demonstrating that it is possible to improve the efficiency and impact on education using distribution and communication strategies (in this case, educational services and content) similar to those used in marketing. The research objective was achieved by a series of technological components and analytic models articulated through a technological platform. A set of digital channels, such as the web and email, facilitated the capture of learning experiences merged with variables related to ubiquitous contexts.

A learning engine maximized the learning process by using the most appropriate channel for each learner profile. By enabling these channels, different variables of the context derived from the data characterized the user's actions. Conventional variables included: location, movement, noise, learning rhythm, individual learning style, preferences in using the content, responses to evaluations, and other elements of virtual learning spaces. Learners could link different virtual elements of their learning (e.g., microlearning) with or without an intelligent engine to personalize or adapt experientially; thereby, motivating satisfactory attitudes, retention, achievement, and overall quality and learning efficiency.

The research experience allowed us to identify and instigate technological challenges with mobile learning and ubiquitous learning. Big Data, advanced analytics, and Artificial Intelligence provided students with an omnichannel learning engine that enabled learning anywhere, any time, and with any device. These characteristics provided experiential learning seven days a week and for 24 hours a day in context, and integrated features, constraints, and conditions related to its use at a given time. These factors ensured improvements in the quality, satisfaction, retention of students, effectiveness, and impact on the virtual learning processes in the Department of Antioquia.

The chapter answers the research Question
What model should integrate elements in intelligently mobile and ubiquitous learning as an articulation of channels, information sources, content for learning, and variables of a digital context-aware following an omnichannel strategy that places the student at the center of the process and responds to their particularities, challenges, and learning place?

The methodology adopted for the project's development was proposed by Hevner et al. (2004). It offered an appropriate paradigm for the study of phenomena of behavioral science and design science. The development of the different activities was accompanied by other methodologies or models of development and innovation including Design Thinking (Lewrick & Link, 2018), Scrum (Schwaber, 2004), Lean Startup (Croll & Yoskovitz, 2013; Ries, 2011), and ASUM-DM (adapted by Angée et al., 2018). The use of these methodologies aimed to achieve a TRL 6-7 product (Hicks et al., 2009).

Background

According to the Colombian National Administrative Department of Statistics (DANE in Spanish), in 2019 the largest population in Colombia were individuals between 14 and 18 years old amounted to 26.1%; and residents between 18 and 26 years represented 16% of the population. These findings suggest that 42.1% of the Colombian population corresponds to people who are part of the "digital natives" generation. Developed characteristics include the "preference for speed, nonlinear processing, multitasking, and social learning, allegedly developed through immersion in digital technology during childhood and adolescence when neural plasticity is high" (Prensky, 2001). Digital natives are hyperconnected by going from one channel to another using different devices and technologies.

The intrinsic characteristics of the target population for distance education programs have not been decisively integrated into the curriculum or its teaching methods. This affirmation is even more relevant when related to virtual programs. Due to their digital nature, virtual programs should be evaluated to consider characteristics highly aligned with the digital natives by integrating multiple channels, resources, and contents. To satisfy the needs of digital natives, it is pertinent to consider the traditional means of virtual education (e.g., MOOC, web, and LMS) and include the additional channels, resources, and interaction mechanisms between students. Furthermore, it must be decided whether the enriched element of virtual education improves learning processes, student retention, and overall satisfaction for digital natives and students of virtual programs (Zmuda et al., 2015).

In Colombia, the Informe Nacional de Competitividad (2017) revealed that the evolution of higher education coverage has accelerated in recent years. The rates went from 37% in 2010 to 51.5% in 2016. While this is above average for Latin America, 51.5% was far below the 76% that corresponds to the OCDE rate. In 2016, the National System for Higher Education Information reported that the coverage in Antioquia was 55%, which was higher than the national average. The Ministry of National Education informed that the country had a dropout rate of nearly half of the tertiary education students. This was due to the advances in coverage, the retention of students, and considering them fundamental for the competitiveness strategy and the *Plan de Desarrollo-Antioquia Piensa en Grande* (2016). We are currently working on solutions to deeply integrate Information and Communication Technologies (ICT) in education because this opens up the possibility of improving the education quality, recognizing students' current contexts, and providing access for more people. In 2016, the UNESCO-UNIR Congress (2016) supported this objective with the following statement: "Education is less and less physical, that is to say, more virtual, through pedagogical strategies it should be possible to overcome the challenges of coverage, access, equity, quality, among others, from the use of ICT technologies".

In general, Colombia and Latin America have introduced distance training programs, with the recent addition of virtual programs, to reach different regions. The Department of Antioquia has experienced an evolution of different training methodologies for higher education. In the 2015-2016 period, there was an accelerated growth of virtual training, coinciding with the increase in coverage of Internet networks after the 2010 launch of the project called Vive Digital of the Ministry of Information Technology and Communications (MinTIC). This project offered significant progress in the massification of Internet use and higher availability of smartphones. According to the MinTIC, the high growth included the number of Colombians who have equipment that allows them to connect to broadband Internet is growing. While in 2015, for every 100 Colombians there were 54.5 terminals, in 2016, the figure rose to 69.55. The advances of virtuality go hand-in-hand with the massification of ICTs and its complete appropriation in education to prompt development. According to the country's digitalization index, the country has reached the advanced stage of its digital ecosystem. This development of infrastructure and access to ICT is viable and imperative to close the gaps in higher education.

Today, the impacts of digital society, technology, and tools for consumers are advancing. An example of these advances is the omnichannel concept. In the past, if a consumer wanted to buy a product, they would go to a local store, view the different options, and make a purchase. As the world evolved, the purchase decision became a little more complicated. The consumer started to get information through other channels such as specialized magazines that offered various products. Then came the Internet which introduced new possibilities for surfing, researching, and buying online.

The evolution continued with the addition of laptops, tablets, and smartphones that give consumers multiple options to meet their purchasing needs. They can choose to shop in the physical store or through a desktop computer, laptop, smartphone, or smart TV. Consumers can interact with social media and discover new products via email, messaging, posting, or by visiting websites with their smartphone, talk to friends about their experiences with a product, or perform other services through different digital channels. Companies that focus on maximizing each channel's performance, store, phone, web, mobile, etc., have a multichannel strategy. An omnichannel approach puts the customer at the center of their strategy. This approach recognizes that customers can be approached or attracted to companies or brands in many ways. The main goal is to create a better customer experience making it appear as if the brand were communicating and working with each costumer. This is possible by providing the user with a more consistent experience. The main characteristics of an omnichannel strategy are:

- The user is the center: This principle is key when creating omnichannel experiences to ensure that a user can finish a process through different means and devices and with no interruptions.

This defines the type of user, their needs, and whether they had a memorable experience when using a channel's services.

- Consistency: It is essential to define the parameters that will help users complete tasks virtually. It must be defined how to take the functionalities to the different points of contact so the user does not have to undertake a new learning process for each of them.
- Neutral information: Starting from the premise of neutral information in an omnichannel project, it will allow similar decisions for certain functionalities that are vital for the users. In this way, clients can go from one point of contact to another without interruptions or delays.
- Context: The all-channel experience must consider the user context. This involves asking questions such as: What data plan will my user have? What device will he/she use? Is he/she a digital native? Will he/she have the level of technology adoption that we need?. The answers to these questions will help define an appropriate road map to make the right decisions for users.
- Availability: This characteristic implies that the correct decisions are being made about the user. It is important to determine the impact that each decision has on end-users. It is also important to define the scope of options that users will have when using select tools to avoid frustrating them in certain moments when they expect functionality and response.
- Strategy: An action plan provides a way to achieve omnichannel experiences that remain in the memory of users. Attention to detail is indispensable. It is necessary to define how to impact people's lives and what added value is available to users. Beyond a clean interface or an innovative design, it has to consider the user's current experience and what will encourage them to return in the future.

Digital natives already use channels such as email and the more popular social networks such as Twitter and Facebook. Students are digital consumers who enjoy more interactive and personalized experiences thanks to mobile and ubiquitous technologies. This leads us to ask if it is possible to use omnichannel marketing strategies to educate better and with greater efficiency and impact?

The benefits of omnichannel and current students' characteristics were the motivating factors for researching and developing a proposal for education. The aim was to provide memorable experiences, centralize information, and integrate different communication channels to offer students information and educational content to solve doubts. The student must be the center of the entire training strategy, both in face-to-face and online education. This facilitated the organization of their learning and the necessary access to the contents of interest. The references for this project's development consisted of 277 virtual education programs offered by 35 Colombian universities. None of the 277 programs had advanced analytic engines, Big Data, or Artificial Intelligence that leveraged mobile learning in a dynamic, personalized, intelligent, and real-time way; allowed the articulation of multiple channels and sources; or dynamically depended on the profile of the students. The channels used in the 277 referenced programs were mostly traditional and unidirectional. None captured the context of the student, even though channels such as intelligent chatbots, bidirectional SMS, telepresence, web services, context geodata, articulation with data of the study environment, among others, could have been used to enrich the experience during the learning process. There were no developments that allowed the articulation of multiple channels in an omnichannel strategy. It placed the student at the center of the learning process and articulated the set of channels, the course content, and other resources according to the student, their needs, requirements, their geodata, and learning style so that mobile learning and experiential and adaptive learning was enabled.

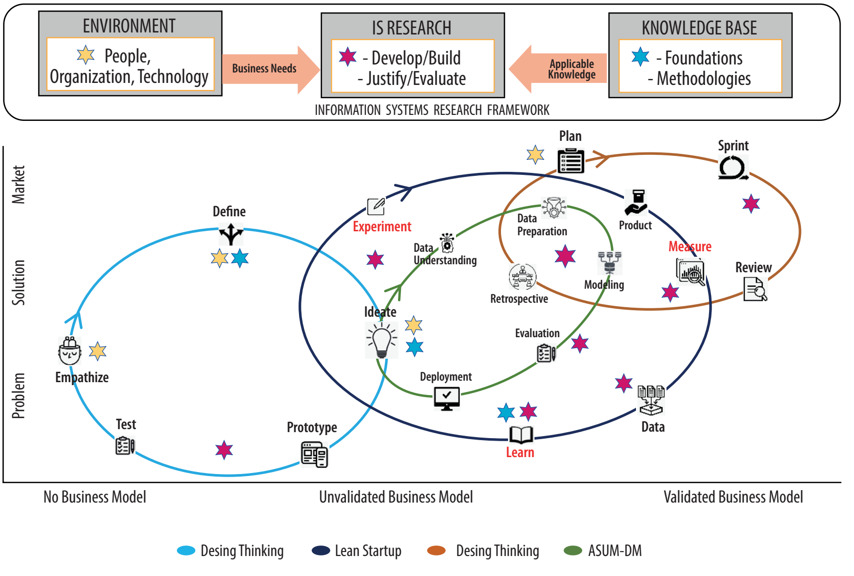
This project focused on developing a virtual education tool that contextualized training processes, customized content, and prompted microlearning from a system that integrated ICT technologies in the educational process. It allowed access to virtual content through different channels and a more significant interaction and collaboration between all educational community members including the institution, teacher, learner, and the environment. This research's novelty revealed the reality of multiple simultaneous training channels under mobile user platforms such as those used today by the industry in virtual training processes. The project complements the tools currently used by the existing virtual education in the Department of Antioquia. It precedes an auspicious moment for both the region and the country by allowing new virtual instruments to reach all regions, in all academic segments. Moreover, it expands its scope to acknowledge disciplines that require contact with physical realities with training programs, which are the fundamental axis of all government plans to create equity and competitiveness.

The research is associated with the challenges established in the 804 Minciencias' call (Colombian Ministry of Science, Technology and Innovation). This project is in the category of Mobile learning in virtual education.

Research Methodology

The proposal is developed by following the Design Science in Information Systems Research (ISR) methodology. Innovation and agile methodologies like Design Thinking, Lean Startup, Scrum, and ASUM-DM support its development. Every methodology provides phases, activities, or elements to perform research and achieve a technology product near the TRL 6-7 innovation context. They interact in a highly iterative loop and each phase provides discoveries that may require revisiting previous steps. Figure 1 illustrates the process.

Figure 1: Design Science in IS Research merged with Design Thinking, Lean Startup, Scrum, and ASUM-DM.



Source: Prepared by the authors

The following describes the main elements of the Design Science ISR methodology and its use through different phases.

Environment

The environment defines the problem space which is composed of people, organizations, and technology. Two groups, the Target Group and the Project Team, are considered. The Target Group consisted of individuals of the learner role. They were identified from the business' needs and classified through the working progress. The Project Team was responsible for creating and evaluating information technology artifacts to solve different government's virtual education viewpoints. The whole team worked with the Target Group to empathize with them and put themselves in the user's position and observe them in detail. The Project Team consisted of four subgroups:

- Creatives: Individuals responsible for understanding the client's educational needs and define the project's basis. They recognize the environment, and establish what the problem is. The group made up of higher education researchers and startups provided ideas that resulted from a research project to achieve an innovative solution. They created the following Researchers, Engineers, and Data Scientists subgroups to be part of the strategic plan and execute the defined activities and achieve the main objective.
- Researchers: Individuals with research capabilities to create new knowledge and scientific outcomes. Senior researchers and postgraduate and undergraduate students are part of this group. They had the responsibility to carry out reviews (e.g., a Systematic Mapping Review) and identify the concepts to be applied and developed in the project. This subgroup is part of the proposed development joined with the Data Scientist subgroup.
- Engineers: Individuals with skills in the design and development of information technology products. They must perform tasks of primary research when new technologies are required to create complex architectures. They must have experience by working with agile methodologies.
- Data Scientists: Individuals with skills in data mining, machine learning, deep learning, and visualization. They worked with data analytics and methodologies as CRISP-DM or ASUM-DM.

The Creatives group executed the phases provided by Design Thinking and Lean Startup methodologies. They began with the Empathize phase to understand the users, their needs, and expectations. Then Creatives and Researchers defined the problem statement that guided the Project Team throughout the design process and the challenges that needed to be addressed. At the Ideate phase, the whole Project Team intervened to propose possible solutions that subsequently turn into prototypes that real users would test. The Prototype phase focused on turning ideas into something tangible, thus allowing the Project Team to gather feedback before developing the whole product. During the Test phase, the Target Group interacted with the prototype by highlighting any design flaws that the Engineer subgroup would quickly fix.

Likewise, the Lean Startup methodology allowed the application of a scientific approach by providing activities to validate each hypothesis proposed by the Researchers and Data Scientists subgroups before further building. This reduced the risk provided by an unknown and uncertain environment. It was the fundamental principle that each hypothesis must be tested and confirmed by experimentation before proceeding to the next phase. We were always sure to build on solid foundations with validated knowledge. The Lean Startup focused on a three-phase circuit that was completed in the shortest possible time and with minimum investment. The Build phase created a product tailored to the customer needs. When data was not enough to create a product wholly adjusted to the Target Group's needs, the idea was to create a minimum viable product. This product must be a version with the minimum functionalities that collected the maximum amount of learning validated about the Target Group. In the Measure phase, the biggest challenge was to measure how the Target Group responded, and, from this data, make appropriate decisions. The Learn phase revealed if the business was viable and would continue to persevere, or if the pivotal ideas were not working properly and needed to be adjusted. In our proposal, the Ideate phase of the Design Thinking methodology provided activities to generate ideas.

In the Plan phase of the Scrum process, a negotiation between the product owner and the team members was performed. During the meeting, the next tasks were prioritizing through a sprint backlog. Each time an idea was accepted, a Sprint was activated by the Engineers subgroup to achieve a small product in a development cycle complemented by other members of the Project Teams. This released the working version of a product more frequently. Once a sprint finished, in the Review activity, the Project Team demonstrated their work results. This allowed for frequent measurement of the project's progress. Then, the Retrospective activity discussed the project process, analyzed what was right, what could be improved, and how to make the teamwork more efficient.

Lastly, ASUM-DM facilitated the implementation of big data and analytic processes. Specifically, this methodology supported data objectives and requirements. The Data understanding allowed initial data collection, as well as identifying data quality issues. Then, in the Data preparation activity, data cleaning was performed. This covered all activities to construct the final dataset from the initial raw data. The Modeling activity allowed us to build models using data mining tools. The Evaluation activity determined if the results met the project objectives and identified the issues that required an early arrangement. Finally, the Deployment activity allowed us to put the resulting models into practice. In this proposal, the Data Scientists subgroup played a significant role by following this methodology's activities.

Knowledge Base

The base of knowledge was to drive through the experiences and expertise of the Project team, mainly from the Creatives and Researchers. Referencing the knowledge base was essential to guarantee that the results are research contributions and the product of the application of appropriated theories and methods. First, a Systematic Mapping Review (SMR) was developed. The objective of the SMR was to trace and categorize the existing literature on mobile learning, ubiquitous learning, and omnichannel for education. This SMR included a systematic search for articles published in high-level journals or events, mainly from 2010. It should report on quantitative or qualitative researches that demonstrated experimentation on topics related to ubiquitous and mobile learning, omnichannel (from retail), context-awareness, and analytical models applied to them. A detailed synthesis of the articles within the different categories identified the potential value and how the search findings would be maximized (O'Cathain et al., 2014). In this stage, the methodologies to be adopted to realize the project were also selected and studied. Subsequently, an analysis of the existing models and tools was carried out.

IS Research

To initiate the proposal, the Project Team devised activities and tasks to develop the ideas defined by the Target Group. The primary outcomes were achieved by using an agile plan that was defined and accomplished to organize the work of the Project Team and Target Group. By taking advantage of functionality as it was implemented and following the expectations of how funding execution must be done, results were then compared to the expected profit. The two main activities carried out at this stage were:

- Develop/Build: End-user motivations and business needs were considered to identify ideas generated by brainstorming. The gathered ideas were transformed into different artifacts such as user apps, channel managers, and an intelligent engine to guide the focus group's learning process. The activity drove the beginning of a business model that could potentially unlock the expected products (TRL 6-7). Here, the agile plan defined sprints including prototyping, experimentation, data understanding and preparation, modeling, measuring (through evaluation/testing sub-tasks), and development.
- Justify/Evaluate: At the end of each sprint, the Project Team reviewed the achieved product to learn from the focus group and determined how it could be improved. Several sprints could be required because the product is defined from the research process.

Literature Review

Different scientific domains have contributed to addressing mobile learning and ubiquitous learning, as well as their challenges throughout the years. Table 1 presents our lines of review with the definition of the main concepts.

Table 1: Literature Review Lines

Learning	Electronic learning (e-learning)	"Learning supported by digital electronic tools and media" (Pinkwart et al., 2003).
	Mobile learning (m-learning)	"e-learning that uses mobile devices" (Pinkwart et al., 2003).
	Ubiquitous learning (u-learning)	"Learning anywhere and at any time" (Hwang et al., 2008).
Context	Context-aware	"Systems that adapt according to the location of the user, the collection of nearby people, hosts, and accessible devices, as well as changes to such things over time" (Salber et al. 1999).
	Context-awareness	Involves adapting systems to the users or their environment by capturing and understanding contexts.
Channel	Multichannel	"Considers the client as the focus of distribution acting and aims at making products available at the greatest number of distribution channels, generating integrated information and, above all, consistent experiences of purchases" (Carvalho & Campomar, 2014).
	Omnichannel	"Integrating the available channels to conquer and adapt to the consumer who demands fast answers and more options from retail" (Carvalho & Campomar, 2014).

Source: Prepared by the authors

Mobile Learning and Ubiquitous Learning

Pinkwart et al. (2003) defined electronic learning (e-learning) as learning supported by digital electronic tools and media. According to Guri-Rosenblit (2005) and González Videgaray (2007), this concept refers to the use of electronic media for different learning purposes, ranging from the classroom's complementary activities to the complete replacement of physical presence. This facilitated online meetings based on pedagogical interactions between students, content, and tutors; therefore, allowing students to interact anywhere using an electronic device.

Pinkwart et al. (2003) and Quinn (2000), defined mobile learning as "e-learning that uses mobile devices". This concept contributed to the development of educational activities through interactions that employ mobile phones and tablets, as well as wireless services. Kukulska-Hulme (2005) and Wu et al. (2012) suggested that mobile learning began as a complement to traditional education when students were no longer able to attend classes in predetermined fixed locations.

According to Hwang et al. (2008), ubiquitous learning is "learning anywhere and at any time" (p. 82). This concept is based on ubiquitous technology facilitating the construction of an omnipresent learning environment allowing anyone to learn anywhere and at any time. To Zhao et al. (2010), a learning environment in ubiquitous learning is defined as any scenario which students can be fully immersed in the learning process.

Al-Emran et al. (2018) presented a review of 87 research articles from 2006 to 2018 about the Technology Acceptance Model (TAM) concerning mobile learning. The research in this area is motivated by the cost involved in technology implementation. Educational institutions must understand the factors that affect the students' acceptance of a particular system before investing a lot of funds for developing or purchasing it. Among the findings of this review, most studies focused on the extent of TAM with external variables, followed by factors from other theories and models, usage measures, and contextual factors. It was also found that the TAM model was extended with factors from other theories and models. The main issue frequently addressed among all the studies reviewed was to examine the acceptance of mobile learning by students. Most of the studies analyzed were conducted in Taiwan, Spain, China, and Malaysia and in the fields of the humanities and educational context, followed by the information technology and computer context of higher education.

Cárdenas-Robledo and Peña-Ayala (2018) conducted a systematic review of ubiquitous learning to research the positive effects on learning outcomes of using mobile learning tools in education. The review proposed TULA's nine categories (physical settings, learning sceneries, functionality, domain knowledge, learning paradigms, effects, academic level, devices, and technology) and the taxonomy for ubiquitous learning approaches. The review analyzed 176 approaches built between 2010 and 2017 and classified them according to the TULA perspective. The authors highlight that the main weaknesses in the area are related to the conception of a model of functionalities to be performed by ubiquitous learning approaches, the design of architectures and frameworks to design approaches, the proposal of software engineering to lead the development of approaches, and standardizing and automatizing the development of systems.

Wang et al. (2017) presented the results of a study on ubiquitous language learning in socio-cultural contexts following three issues: system usefulness, activity usefulness, and activity playfulness in museum learning. The authors examined 12 works achieved between 2009 and 2014 related to mobile technology-supported language learning in museums. An important aspect discussed in the study is how location-based mobile applications transformed users from passive receivers to active learners. Many of the museums adopted ubiquitous location-based systems using mobile devices to strengthen social ties when students collaboratively worked to perform language learning activities.

Lucke and Rensing (2014) performed an extensive survey on mobile learning and categorized the analyzed works concerning educational settings and the main pervasive technologies used. The authors mentioned software and hardware in their list of areas for future research in mobile learning, concluding that pervasive education will result in a fusion with traditionally isolated education on-site settings could be enriched with information technology, and face-to-face activities could be improved with virtual settings. The authors encouraged researchers to innovate in e-learning through pervasive education, context-awareness, adaptivity, and immersive experiences.

Verbert et al. (2012) presented a survey of context-aware recommender systems that have been deployed in Technology Enhanced Learning (TEL) settings. The survey outlined areas where further work is needed. The authors identified relevant context dimensions for TEL applications, then analyzed existing TEL recommender systems along these dimensions. Finally, they highlighted topics where further research was needed to include context data acquisition, contextual data representation, evaluation studies that assess the impact of individual context elements on the recommendation process, data set shares, privacy, among others.

Martin et al. (2011) investigated the frameworks and middleware systems for facilitating and simplifying mobile and ubiquitous learning applications development. The analysis focused on operating systems, programming languages, and the primary purposes of the studied systems. The authors concluded that further development is needed in frameworks and middleware systems devoted to facilitating the creation of mobile and ubiquitous learning applications to consider different sensors, learning objects, services, standards, and platforms for mobile and ubiquitous learning. There is a lack of advanced frameworks that encapsulate the complexity involved in dealing with different sensors. Other fields to be explored are the privacy and security to build systems that guarantee the user's rights.

Context-awareness

The term context-aware is defined by Salber et al. (1999) to describe "systems [that] adapt according to the location of the user, the collection of nearby people, hosts, and accessible devices, as well as [...] changes to such things over time". Context-awareness tends to involve adapting systems to the users or their environment by capturing and understanding contexts. According to Byun and Cheverst (2004), a learning system is context-aware if it can be extracted and interpreted and its contextual information can be used to adapt its behavior and functionalities to the current context. According to Siadaty et al. (2008), in mobile and ubiquitous environments, the context is summarized in the spatial and temporal aspects of the user's situation. Hwang et al. (2008) give a special definition of ubiquitous learning through the concept context-aware u-learning, which is the employment of "mobile devices, wireless communications and sensor technologies in learning activities" (p. 83). Context-aware analysis in teaching-learning processes has evolved significantly in several emerging fields such as Context-Aware Mobile Learning Applications (CAMLA). The systematic literature review presented by Kumar and Sharma (2019) describes the key components of CAMLA through the extraction and representation of context information, context adaptation, and different types of applications developed. The review identifies different context types of which the student, location, and time are the most frequently used types in CAMLA development.

Hasanov et al. (2019) presented a literature search on Adaptive Context-Aware Learning Environments using a meta-analysis of 53 studies published between 2010 and 2018 identifying variables such as mobile devices, Radio-Frequency Identification, Near-Field Communication, ontology for context modeling approach, context data from the student's profile or location, rule-based adaptation, and informational feedback. The authors proposed a taxonomy of context-aware categories allowing them to propose recommendations for future context-aware research on the adaptation of educational applications.

The work presented by Muñoz and González (2019) evaluated and discussed common components in context, feedback techniques, and modeling. They concluded that the most relevant context entities are time, location, device, environment, and the student. The components in common include content delivery, student profiles, context acquisition, question banks, adaptive evaluation, reasoning modules, and feedback modules.

The paper presented by Nye (2015) proposed a literature review on trends and approaches in educational technology. The review focused on the barriers to adopting intelligent tutoring systems and could be applied to any type of educational technology analysis. These barriers included students' basic computer skills, hardware sharing, mobile device restrictions, data costs, electrical reliability, internet infrastructure, language, and culture. The differences and similarities between externally and locally developed tutoring systems were considered. The review concludes with possible future directions and opportunities for research on tutoring systems and other educational technologies on the global stage.

The review by Verbert et al. (2012) assessed the degree of analysis of variables in recommendation systems research for TEL processes. They presented a context framework that identified relevant context dimensions for TEL applications. Based on the results of the review, they describe some issues for which additional research is needed.

Moreover, the systematic review presented by Alsswey and Al-Samarraie (2019) identified influential factors and challenges affecting the adoption of mobile learning among the students at universities in Arab Gulf Countries (AGCs). The authors explored the current evidence on the use of mobile learning in AGCs. The results show different factors (i.e., cultural, and social) that contributed to the acceptance/adoption of learning in AGC universities.

The systematic review of Khanal et al. (2019) explored the mobile learning's adoption learning using a selection and analysis methodology for extracted publications, focusing on the publication trend, the adoption models used, and a set of factors influencing the adoption of mobile learning.

Multichannel vs. Omnichannel

According to Carvalho & Campomar (2014), in marketing "the multichannel has a premise to consider the client as the focus of distribution acting and aims at making products available at the greatest number possible of distribution channels, generating integrated information and, above all, consistent experiences of purchases" (p. 103). Furthermore, to Kotler and Keller (2012), each channel has a specific target segment and companies must be careful to ensure that customers can interact through their preferred channels. Additionally, Juaneda-Ayensa et al. (2016) defined omnichannel strategy as

> a form of retailing that, by enabling real interaction, allows customers to shop across channels anywhere and at any time, thereby providing them with a unique, complete, and seamless shopping experience that breaks down the barriers between channels (p. 1).

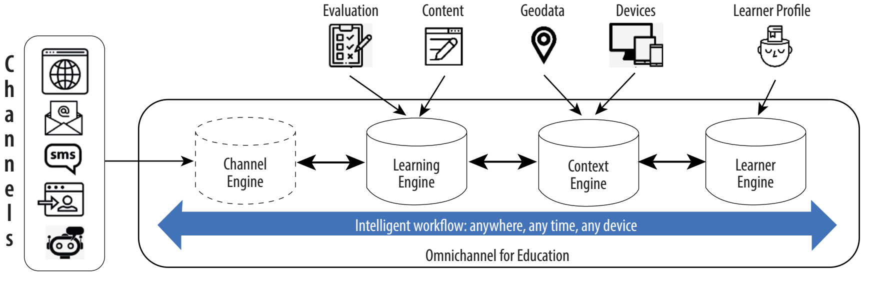
Omnichannel retailing is a phenomenon produced by the emergence of channels and new technologies that allow retailers to integrate all the information these channels provide (Brynjolfsson et al., 2013). Parente and Barki (2014) mention that clients can access the online information concerning the products even when they are inside a physical store and have contact with countless information including promotions, prices, advantages, and negotiations. According to Carvalho & Campomar (2014), omnichannel "aims at integrating the available channels –physical and virtual ones– in order to conquer and to adapt to the consumer who demands fast answers and more options at the retail" (p. 103).

Based on the concepts and works mentioned above, we identified areas within ubiquitous learning that are currently deemed challenging so that further research and development in these fields could be explored. The previous reviews provided an important research synthesis on mobile learning and ubiquitous learning by analyzing various research articles. It has been observed that research has overlooked the review of context dimensions and the relationships between them. This is what motivated us to conduct this SMR. This review attempts to add value to the existing reviews by including an up-to-date synthesis of ubiquitous learning research articles mainly based on context-awareness. In contrast, we did not find works related to omnichannel for education.

Omnichannel for Education Proposal

This section describes the components of an innovative product achieved through the aforementioned research methodology. Figure 2 shows the global vision of the proposal for applying omnichannel for education.

Figure 2: Omnichannel for Education proposal



Source: Prepared by the authors

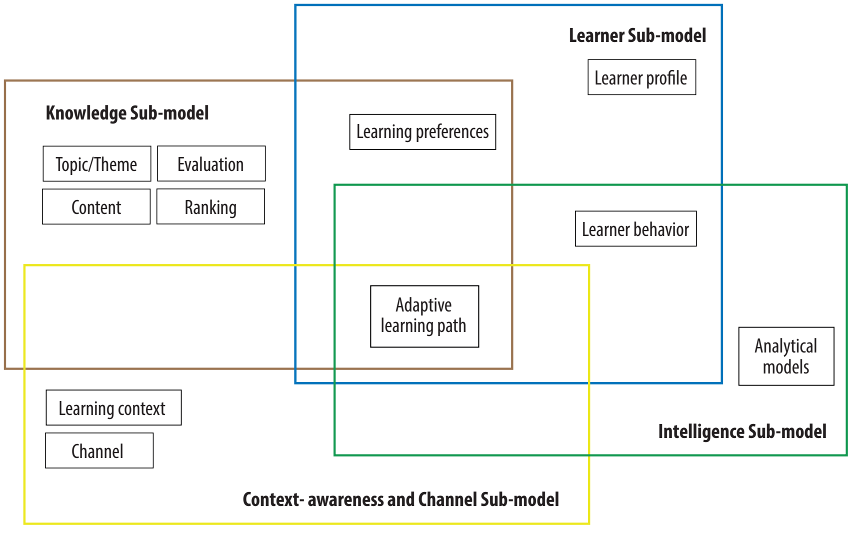
The proposal's components allowed us to manage information about learners, context-awareness, learning process, and channels through different engines to define and support the student's learning process.

- Learner Engine: Identifies the characteristics and particularities of the learners as personal information.
- Context Engine: Oversees the capturing of information from the learner's context in which the contents are used such as geolocation, device, Internet network quality, and ambient noise.
- Learning Engine: Provides study contents and evaluations to the learners.
- Channel Engine: Responsible for managing and articulating channels to achieve the omnichannel proposal according to each student's particularities based on the results of the Learner Engine. In this chapter, only web and email channels were tested.

These engines take an intelligent shape through a workflow that manages the main omnichannel characteristics. To develop and deploy the above-defined components, a research product called Omnilearning application was created. This web application provided a context-awareness environment where processes of mobile learning and ubiquitous learning could be analyzed. A set of context variables were captured in real-time where learners could document the learning workflow throughout a microlearning proposal consistent of videos and PDF files that motivated him/her to learn about a topic under his/her learning style. A set of interactions were prepared in the microlearning where learners provided data to an adaptive learning system, which suggested an improved action to the learner. The most appropriate assessment provided was in accordance to their profile, geolocation, and the most relevant available contents.

Figure 3 shows the main research components that guided the building of the application. It corresponds to a conceptual model designed to explain how channels and engines of Figure 2 work to guarantee an intelligent workflow that the student can follow anywhere, at any time, and using any device. A set of sub-models define the conceptual model. All of them have a set of entities that define the sub-models, functionality and dynamic interaction with each other.

Figure 3: Conceptual Model of a Learning Engine.



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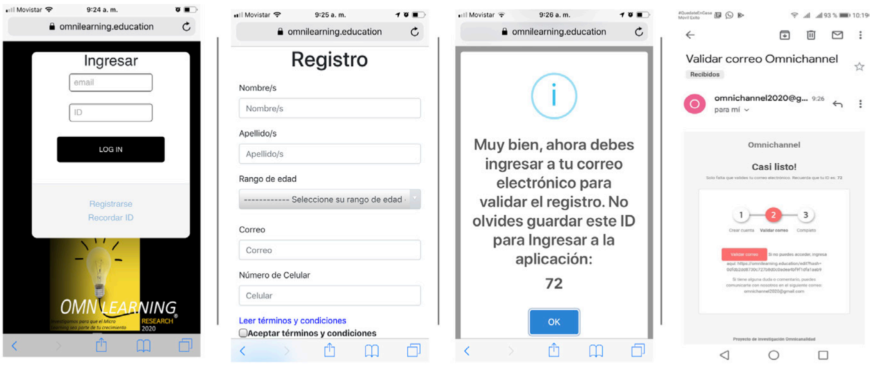
The Learner Sub-model

The learner is the central element of the proposal. Entities and their characteristics in the sub-model allowed us to find particularities by using analytic models that could lead to personalized instructions. Figure 4 represents the user interfaces where learners registered personal information.

Figure 4: User Interfaces to capture personal learner information.



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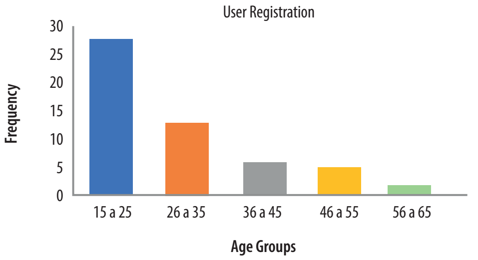
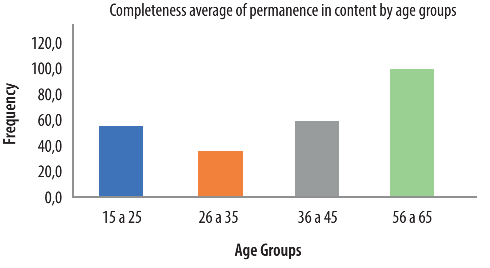
Once the learner is an Omnilearning application user, he/she can be profiled according to age. This is a way to understand why the learner chooses a learning path and allows the application to apply descriptive analytics models by finding adaptive alternatives to improve or personalize his/her learning style or opportunities. A pilot test of the Omnilearning application included a sample of 54 students of ICT and related areas. Those students were members of the Target Group and were between 15 and 65 years old. Figure 5 shows three plots that allow understanding the distribution of the learners by age groups. Figure 5(a) shows the age distribution of the people registered in the application during the pilot test. This allowed us to have an early learner's profile. Figure 5(b) shows how the learner age groups have accessed the contents. Figure 5(c) presents how the age groups' learners have advanced in the use of contents provided in the learning paths. For instance, a frequency value equal to 100 represents an age group that has accessed one or more contents entirely.

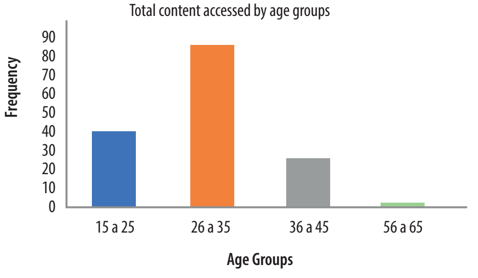
Figure 5: Descriptive analytics models by age groups.



(a) Learners registration.



(b) Content access.



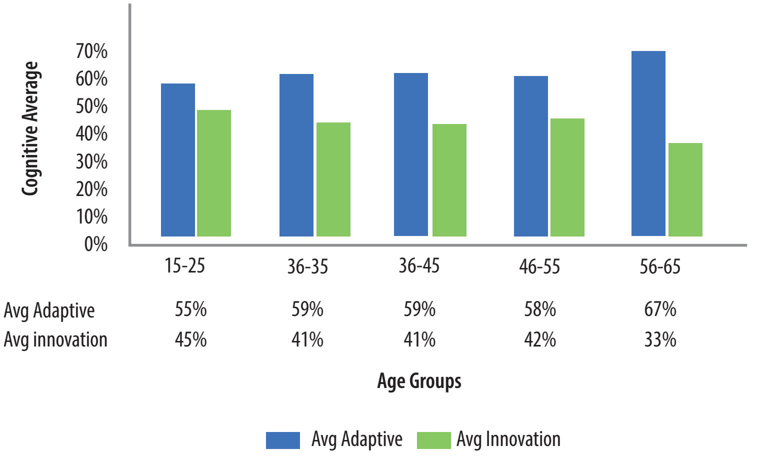
(c) Completeness of permanence in contents.

Source: Prepared by the authors

Likewise, a learner can be profiled by his/her cognitive style, which is related to the structure the learner prefers when solving problems, making decisions, and processing information. These preferences varied across a broad spectrum ranging from highly adaptive to highly innovative. Bobic et al. (1999) proposed three dimensions of the Kirton Adaptation-Innovation Inventory where 32 items were grouped: Rule/group conformity, Efficiency, and Originality.

It is simplified by choice-pairs of nine multiple selections to create an alternative measure (Altkirt). At one point in the pilot test, part of the Target Group (54 participants) had filled out the application responding to each of the nine proposal points. Figure 6 shows a comparative analysis showing the tendency for individuals to have an adaptive behavior. In other words, they are disposed to have a viewpoint characterized by reliability, efficiency, prudence, discipline, or they are more interested in solving problems rather than finding problems to solve. The innovator profile is determined by other cognitive characteristics that could identify him/her. It could drive the way on how learner knowledge points at preferences about a topic.

Figure 6: Cognitive style by age groups



Source: Prepared by the authors

The Knowledge Sub-model

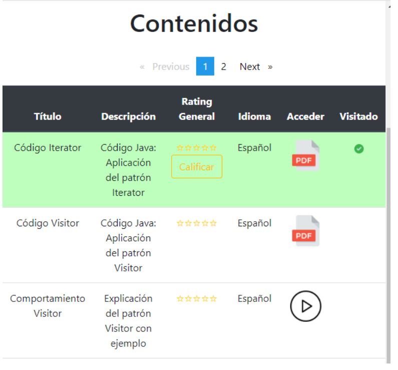
This sub-model describes the knowledge resources that represent the structured domain knowledge (theme and topics associated with the theme) and the content that facilitates the appropriation of the concept by the learner.

Each topic has been structured considering pedagogical aspects such as learning objective, level of knowledge (basic, intermediate, advanced), logical sequence of the topic, and the set of questions that allow evaluating the learning of the topic. Each content is characterized by its category and type. The content category is associated with the preferred way of learning and has been defined in four categories: Motivation (introduction to the topic), Technical definition (definition of one concept), Example (implementation of a concept), and Code (implementation of a concept). On the other hand, the content type defines the different formats in which the content is presented. Another important entity of the knowledge model is the content ranking which helps measure the learner's perception of the contents.

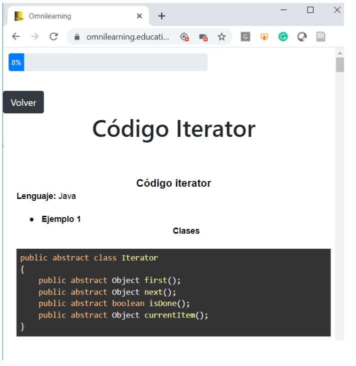
The definition of the knowledge model is accompanied by its implementation in the Omnilearning application. A set of microlearning units define the topics and their contents. Following Göschlberger & Bruck (2017), "microlearning refers to a didactic concept and approach that uses digital media to deliver small, coherent and self-contained content for short learning activities" (p. 545). Microlearning has become popular mainly due to the increase in the number of mobile devices and because it brings new possibilities for tracking learner activities and progress. The content is organized into short 2 to 10-minute video lessons.

Figure 7 illustrates an example of the educational contents of the application. The content structure is based on the topic called "Software Design Patterns", which is distributed over four iterations: General aspects, Creational Patterns, Structural Patterns, and Behavioral Patterns. The learner can visualize his/her progress through color-coded graphic elements including the percentage of content not yet accessed (white), 50% or less of content accessed (yellow), and content fully accessed (green); the content visited progress bar; and an immediate display of the evaluation score.

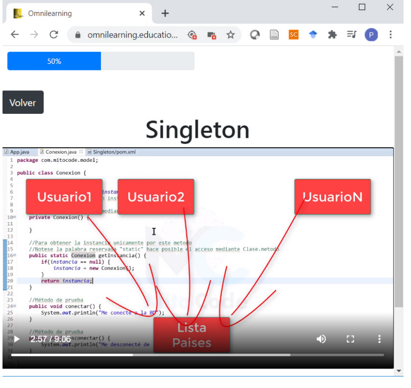
Figure 7: User interface of Contents and Evaluation.



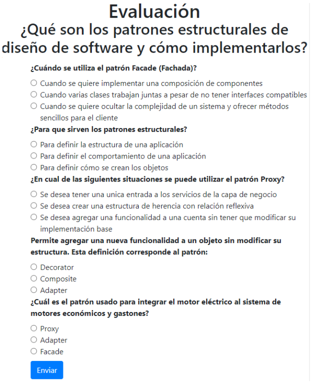
(a) Contents list view.



(b) PDF content example.



(c) Video content example.

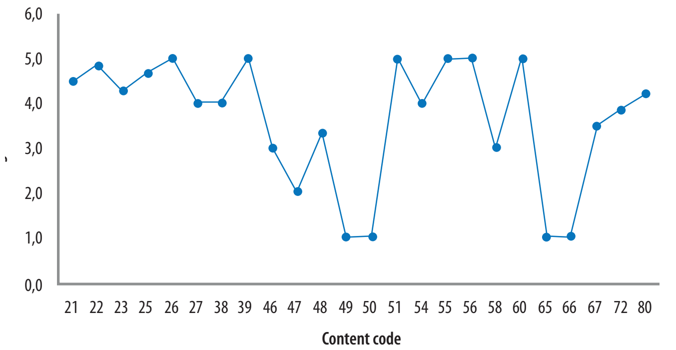


(d) Evaluation example.

Source: Prepared by the authors

When a user uses a content, he/she can vote depending on their satisfaction with the content. The vote is represented at 0 being the lowest score and 5 being the highest. Figure 8 presents the rating distribution of the contents. It also indicates the percentage of permanence in each content, where 100% represents that the content was viewed in its entirety. In general, the highest marks are given to content that was viewed for more than 50% of its total duration.

Figure 8: Content Rating



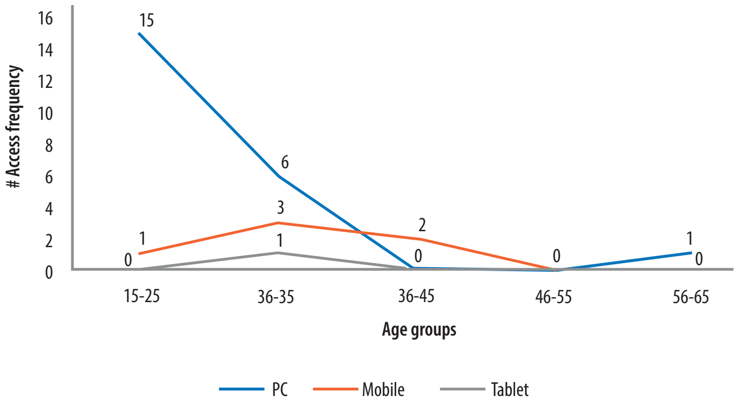
Source: Prepared by the authors

The evaluation allowed us to verify the understanding of the learner. In Omnilearning application, there is one evaluation for each iteration. An evaluation consists of five multiple-choice questions randomly selected and connects to information presented in the contents. There will always be at least one question related to a technical definition, at least one related to an example, and at least one related to a code presented in the contents. The learner has three opportunities to pass the evaluation. Each time he/she performs the evaluation, he/she receives the result, as well as the best obtained result.

The Context-Awareness and Channel Sub-model

This model represents the process of monitoring the environment's variables to identify special conditions that originate the automatic adaptation of the content type that will be presented in the personalized learning path. The omnichannel communication represents the technological mediators that facilitate the learning process by eliminating the barriers of time and space, and captures the context variables to achieve context-awareness anywhere, at any time, and with any device. In this work, we managed three types of channels: mobile, web browser, and email. Figure 9 illustrates the device usage by age groups.

Figure 9: Device usage by age groups



Source: Prepared by the authors

According to El Guabassi et al. (2018), the learning environment or learning context represents the attributes of a learning session (Mobility, Luminosity, Noise, Internet connectivity, and Location) which is monitored through context-awareness technology for a specific learning session. The learner's activities and achievements are monitored and analyzed to identify the characteristics of the context in which the student performs the learning activities. This monitoring also allows for analyzing the relationship between the characteristics of the context and the student's final achievement. The Omnilearning application captures the following context variables:

- Location (latitude and longitude): The places where the learner uses the application to access its contents or to carry out evaluations.
- Ambient noise: Captures the noise (in decibels) of the learner's study environment.
- Device type: Indicates whether the learner is connecting from a cell phone, a tablet, or a computer.
- Battery Level: Captures the battery level of the device used by the learner.

- Network speed: Indicates the learner's Internet network speed. The possible values are 2g-slow, 2g, 3g, and 4g.
- Accelerometer: Indicates if the learner makes any moves when accessing a content.
- Time in each content: Captures the time spent on the visited contents.

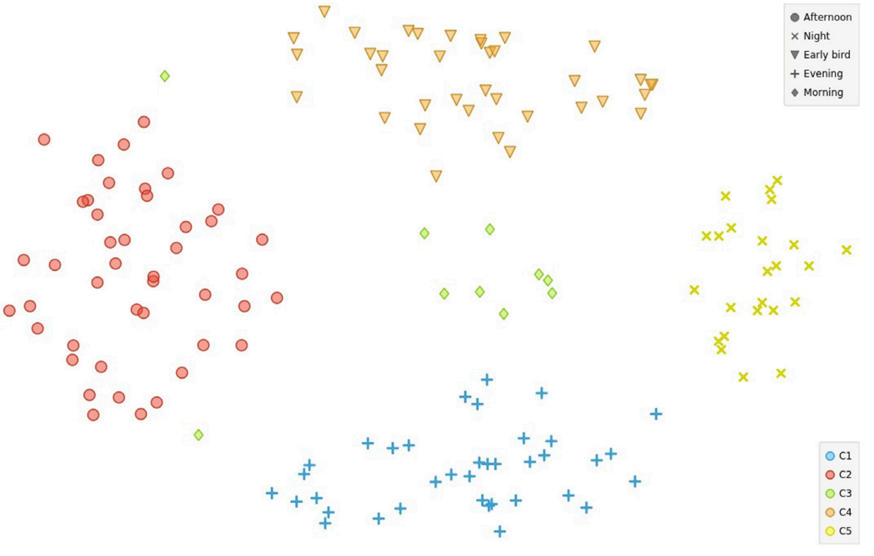
Other aspects that characterized the learner (adaptive learner path, learner profile, and learner behavior) were obtained through an analytical process based on data generated by the iteration and will be explained in the Intelligence sub-model. From the selected topic, the system generates the learning path that the learner must follow. The topic is associated with a learning iteration which is overcome when the learner answers the evaluation associated with the iteration (learning assessment).

The Intelligence Sub-model

This sub-model defines the analytic and machine learning models needed to characterize the learner's behavior, context-awareness during the learning process, the learner's learning style, the management of learning path contents, and its impact on the results measured by the evaluation proposed at the end of each microlearning course. Understanding, preparing, and evaluating the behavior of data and their support to the decision-making are the main functionalities of this model. At the same time, the collected data and other required models could adapt the knowledge resource to different contexts to provide learners with the best match for their current situation. For instance, Figure 10 shows five clusters that represent learning periods where a set of users accessed different contents. These timeslots are defined in the following categories:

- Early bird: 00h - 06h
- Morning: 06h - 12h
- Afternoon: 12h - 17h
- Evening: 17h - 21h
- Night: 21h - 00h

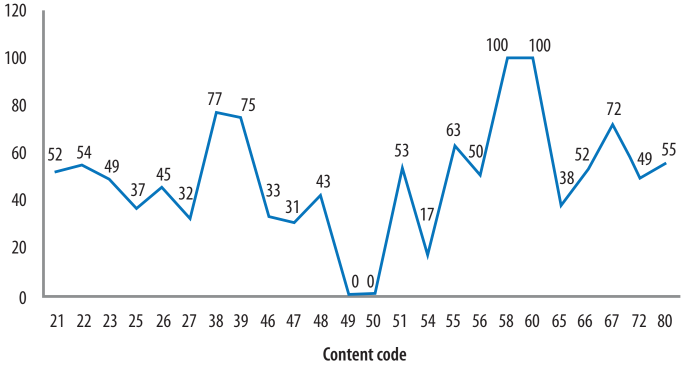
Figure 10: Clusters of Learning periods preferred by learners



Source: Prepared by the authors

Figure 11 shows two dispersion plots that allow us to understand how learners perceived the contents.

Figure 11: Permanence in preferred contents



Source: Prepared by the authors

Results and Conclusion

The integration of diverse methodologies for the development of our proposal generated a dynamic teamwork by improving communication, team collaboration, and maintaining constant interaction with the Target Group. Design Thinking and Scrum followed a user-centric approach which allowed the Project Team to have a direct relationship with the Target Group, making it easier for the resulting product to satisfy their needs completely. Simultaneously, Lean Startup and ASUM-DM allowed for scientific experimentation to guarantee a quality product completed in a short period.

The Project Team confirmed that this proposal is two-fold, meaning:

- A proposal based on three pillars: the student profile, the knowledge resources (contents) and context-awareness management, and the omnichannel communication mechanisms. These pillars were centered on the learner and their learning profile to optimize his/her learning. The conceptual model allowed the learner to follow a flow of access to content anywhere, any time, and from any device.
- The implementation of the proposal in the Omnilearning application and the initial experimental results were obtained from a case study with ICT students.

Bearing in mind that our target audience was primarily digital natives, our proposal integrated features for users to feel more motivated to use it. For example, the Omnilearning application provided immediate feedback regarding student progress through graphic elements such as the percentage of content represented with white, yellow, and green colors; a content visited progress bar; and the immediate display of the evaluation score. It also provided microlearning spaces to encourage student concentration and generated challenges and ways to establish new learning styles. The elements were accessible through mobile devices.

Regarding the question: Why not use omnichannel marketing strategies to educate better and with more coverage and greater efficiency and impact?, our proposal applied some of the characteristics of omnichannel in an educational context. The Omnilearning application distributed information to the learners through different channels:

mobile (access to the Omnilearning application and all its features), web browser (access to the Omnilearning application with limited access to contextual awareness functions), and email (communication of important milestones such as completing an iteration or the outcome of an evaluation). In conclusion, it is possible to improve the efficiency and impact on education using distribution and communication strategies like those used in marketing. These characteristics provide experiential learning and identify the restrictions and conditions related to its use at any given time.

Research Question Answer

The conceptual model that integrates elements in intelligently mobile learning and ubiquitous for articulating channels, sources of information, content for learning, and variables of a digital context-aware, following an omnichannel strategy, is compounded of a Knowledge sub-model, a Learner sub-model, a context-awareness and Channel sub-model, and an Intelligence sub-model.

The proposal integrated the main characteristics of omnichannel to guarantee that the learner was the central element. The main objective was to offer him/her an appropriate learning experience according to the context's characteristics. The application followed consistency and defined the parameters that helped the user complete tasks practically preventing the user to have to undertake a new learning process when accessing from a different device. The proposal considered the context essential and helped define an appropriate road map to make the right decisions for the learner. The application followed a pedagogical strategy that guided students in their learning process through the proposed contents and evaluations.

The research results proved the significant contribution of omnichannel strategies in education. Simultaneously, it proved a direct relationship between learners and mobile devices used during the learning process. The context variables and final students' outcomes provide new knowledge to the decision-making. This research also highlights the way how many technologies and tools can be successfully involved in the learning process and provides a straightforward application of modern educational ubiquitous and mobile approaches.

Further research and development will focus on:

- Products of new knowledge and dissemination: articles published in high impact journals, and articles in events.
- Knowledge dissemination products: seminar on technology.
- Knowledge network.
- Technological development and innovation products.
- Integrate more channels such as chat, chatbot, two-way SMS, landing pages, voice, among others to facilitate the capture of information through the interaction of individuals with available digital content, and a ubiquitous context-aware.

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Fostering intuitive knowledge of multivariable calculus concepts using a collaborative augmented reality application

DOI: https://doi.org/10.17230/9789587207002ch3

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Introduction

Education has been constantly evolving along with many other human processes and activities. Computers are now key elements within the learning process that help educators and students attain academic goals. Whilst some tools are developed for strengthening soft skills (Holzapfel, 2018; Manyika et al., 2017), others assist students in different learning areas. Universities as well as primary and secondary schools have identified that certain technologies are useful to support the teaching–learning process (Rickel, 2001; van den Berk, 2015).

Mathematical concepts are, in some cases, abstract and not easy to understand and visualize. Calculus, and multivariable calculus in particular, is an example of such a complex area (Orozco et al., 2006). Trying to draw a 3D surface on a 2D plane, such as a whiteboard or a piece of paper, is, in many cases, difficult and hard to achieve as well as time-consuming and not efficient. There are some tools available in the market that help educators teach some calculus concepts, such as GeoGebra which is a powerful and useful tool but is still a 2D representation of a 3D surface (Di Serio et al., 2013; Freina & Ott, 2015; Ibáñez & Delgado-Kloos, 2018; Ibáñez et al., 2020; Volkow & Howland, 2018).

Virtual and augmented reality technologies (VR and AR, respectively) are having a huge impact on many aspects of human life, one of them being education (Azuma et al., 2001; Burdea & Coiffet, 2003). They provide environments that help students overcome some of the problems mentioned above (Giraldo et al., 2007; Pan et al., 2006; Velev & Zlateva, 2017) and increase motivation in both educators and students (Jensen

& Konradsen, 2018). There are different technologies that support VR experiences: some of them track only users' head movements, while others track their whole-body movements. The type of tracking seems to have an impact on the students' learning process, as suggested by Alhalabi (2016).

This study describes the development of an AR-based tool that helps calculus teachers and students reach a desired academic goal, aiming to achieve a high level of acceptance of, satisfaction with, and motivation in the teaching–learning process.

This article is organized in the following sections: *Related Work* introduces the state of the art of the use of technologies, mainly AR, within the educational world; *Description of the AR Application and its Validation* describes the usage and development of the application and how it was validated. The section *Results* presents the impact of the application among the selected group of students, through statistical calculations. The last section of this article is *Conclusions and Future Work* which contains the outcome of this research and how it is going to move forward.

Related Work

When students approach advanced studies in Science or Engineering, they have a large corpus of nonformal (intuitive) knowledge, acquired from their interaction with the natural world (Chudnoff, 2013). In some cases, this intuitive knowledge must be unlearned; for instance, when the formal knowledge to be acquired is counter-intuitive, such as the quantum phenomena at the sub-atomic level. In most cases, creating associations between the previously acquired intuitive knowledge and the concept to be studied helps students approach the learning process and acquire the necessary ulterior formalization. In the area of Physics, a study (Sherin, 2006) describes how the previous intuitive knowledge that physics students have acquired helps them by providing context to the interpretation of the physics problems presented to them.

There has been a revival of interest in VR and AR technologies, particularly for educational purposes (Chen et al., 2017). Multiple factors explain this revival: one of them is the availability of more powerful yet less expensive hardware that can render quite complex scenes and 3D objects; another is their business potential: various sources predict the VR/AR market to grow to 161.1 billion US dollars by 2025 (GlobeNewswire, 2020). One of the most appealing uses of VR/AR is in education and training: VR/AR technologies can be used to teach procedures and concepts, increasing the users' engagement and immersion, while reducing risks and costs.

Augmented reality is being used more and more in educational settings. Ibáñez & Delgado-Kloos (2018) found 28 studies using AR to support the learning of Science, Technology, Engineering and Math (STEM) concepts. Most of the studies aimed at allowing students to learn through exploration or simulation activities. The reported studies prove that "augmented reality technology fosters positive affective states of students, such as motivation, engagement, and attitudes toward STEM subjects that have proved to be effective in promoting learning benefits" (p. 12). The study by Martín-Gutiérrez et al. (2015) shows that AR can be used effectively to promote autonomous learning in higher education.

Our work differs from the above in that we created and validated an AR application specifically to develop intuitive knowledge of multivariable calculus in first-year engineering students. The specifics of the study are described in the following section.

Description of the AR Application and its Validation

To provide students with a 3D visualization of the surfaces and planes, a collaborative AR application was created using Vuforia for visualization and Photon for collaboration. The application allowed the instructor to create a function of the form

$$z = f(x,y)$$

After the instructor entered the function, all participants were able to observe, through their cell phones, the corresponding 3D surface rendered on top of a printed pattern, which was typically placed on top of a table in the middle of the classroom (see Figure 1).

Figure 1. Student holds his cellphone in his hand, pointing at the pattern. Note the 3D surface that is rendered on the cellphone

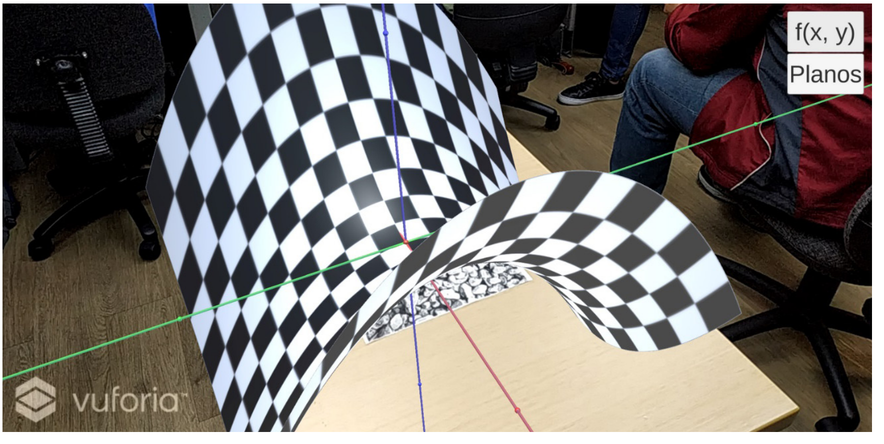
Source: Prepared by the authors

Development of the AR application

The application provides support for two distinct types of user: instructors and students. Instructors are responsible for creating the "room", i.e., the shared virtual space in which the collaboration messages are broadcast. After the room is created, instructors enter the equation of the surface to be visualized. The instructor can restrict the domain of the x and y variables, and scale the surface to be larger or smaller, to create a better visualization. After joining the virtual room, students visualize the surface that the instructor has added. Both the instructor and the students can point at any arbitrary area in the shared surface, touching their cell phones with their fingers. When a user X points at an arbitrary area, other users visualize a "ray" originating at X's cell phone and intersecting with the surface. This allows every participant to see where participant X is pointing at. It is important to mention that this functionality allows for a remote usage of the application where users could be at different physical locations.

To facilitate the definition of the function to be visualized, a parser was created. The parser recognizes functions including polynomials and trigonometric functions. After being parsed, the function is evaluated at various points of the XY plane, and a polygon mesh, representing the surface, is created (see Figure 2).

Figure 2. 3D rendering on the AR application of equation $z = x^2 - y^2$



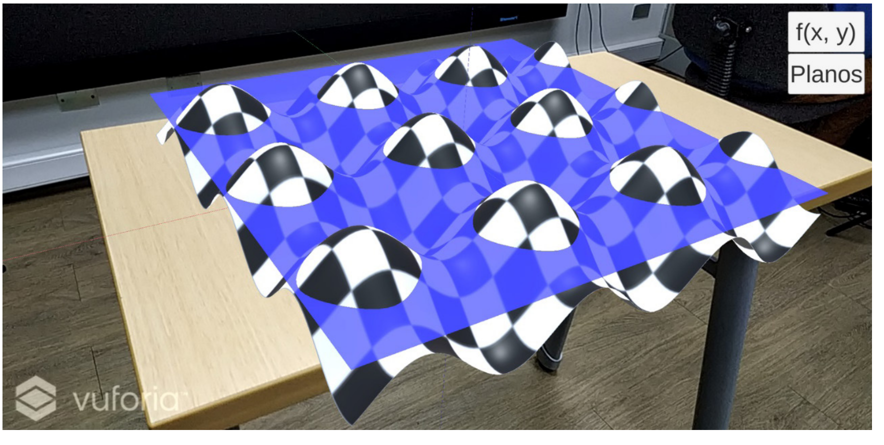
Source: Prepared by the authors

The AR application, was built using parts of several existing applications: Vuforia (https://www.ptc.com/en/products/vuforia), Photon (https://www.photonengine.com/) and Unity (https://unity.com/) frameworks. It was run on the students' Android mid-range cell phones without any major inconvenience. The limitation on the number of users permitted by the free version of Photon was not a problem, since the virtual rooms were shared by no more than 10 simultaneous users.

Pedagogical use of the AR application

After the initial setup, the instructor asked the students to observe the surface from various points of view. In the case of the hyperbolic paraboloid depicted in Figure 2, the instructor asked students to describe the parabolic curves forming the surface when observed from the X axis, shown in red (opening up), as opposed to the parabolic curves forming when the surface is observed from the Y axis, shown in green (opening down). The instructor asked students also to cast rays that moved away from the midpoint of the surface ($x = 0$ and $y = 0$) in the direction of the X axis, and showed them that they would be going "up," as opposed to moving away from the mid-point in the direction of the Y axis, in which case they would be going "down." The instructor used this activity to show students the intuitive concept of partial (and directional) derivatives. Students answered questions asked by the instructor to reach consensus on the explanations. Similar guided experiences were used to introduce the concept that the intersection between a 3D surface and a plane, if it exists, forms one or several curves in space (see Figure 3).

Figure 3. Intersection of the function $z = \sin(x) + \cos(y)$ and a plane that is parallel to the XY plane



Source: Prepared by the authors

We believe that it is the self-reflection process, undertaken by the students during the collaborative session, and supported by the technology, that enhances their understanding of the topic at hand. It is, therefore, not the technology by itself, but in combination with an appropriate pedagogical approach that is pedagogically effective.

Pedagogical validation of the AR application

Users with no knowledge in calculus (first-year students) were asked to complete pre and post-test evaluations. Pre and post-test evaluations contained the same questions but were presented at different times and aimed to measure the knowledge acquired during the experience. The questionnaire was designed by the researchers because of the need to address very specific knowledge of multivariable calculus in several questions, while, in others, addressing specific motivation questions.

Questions in bold are the ones considered for measuring the knowledge variation (delta) (see Table 1).

Students also completed questionnaires that aimed at evaluating their subjective perceptions of the experience. The questionnaires are built as a set of affirmations and students choose options from a Likert scale. The following topics were explored in the questionnaires:

- Personal satisfaction
- Relevance of the tool
- Personal perception
- Tool's usability
- Learning
- Motivation
- Attention in classes (during the lecture)
- Attention in classes (during the activity)

Results

This section presents the results of the students' assessment, both on the level of knowledge before and after the intervention and on the students' perceptions of the application.

Table 1. Questionnaires that students completed before and after the pedagogical intervention

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In the following questions, you will read about a series of situations regarding calculus and surface calculus. Answer freely. Answers will be used for research purposes only.

In each case, please select at least one option and indicate any others you consider relevant.

1. Some everyday situations in which calculus is applied are:

   a. For calculating volumes.
   b. For finding tangent planes to a surface in each point on the surface.
   c. For finding maximum and minimum points along a function or surface.
   d. Other: ____

2. Some specific situations in which you have used calculus outside academic work are:

   a. Personal work.
   b. In the development of a personal hobby.
   c. None.
   d. Other: ____

3. In your surroundings (home, university, city) is there any surface that you could describe with equations or calculus functions?

   a. The roofs of some building.
   b. Some ornamental figures.
   c. I have not seen surfaces that could be described with calculus equations.
   d. Other: ____

4. Do you think that the study of equations through calculus can help in the understanding of concepts within other courses or modules of your course?

   a. Velocity.
   b. Acceleration.
   c. Direction.
   d. Other: ____

5. Studying and understanding surfaces through their equations is important because they allow me to:

   a. Model my surroundings.
   b. Build 3D scaled models.
   c. Calculate maximum, minimum and saddle points.
   d. Find directions of points within the surface.
   e. Other: ____

6. If you are standing on a surface, in what way could you determine, if it exists, if there is a maximum point or points on it:

    a. If you observe, from all surface points, that to reach that point you have only a positive slope.
    b. If you observe, from all surface points, that to reach that point you have only a negative slope.
    c. If you observe, from all surface points, that to reach that point you have negative and positive slopes.
    d. Other: ____

7. If you are standing on a surface, in what way could you determine, if it exists, if there is a minimum point or points on it:

    a. If you observe, from all surface points, that to reach that point you have only a positive slope.
    b. If you observe, from all surface points, that to reach that point you have only a negative slope.
    c. If you observe, from all surface points, that to reach that point you have negative and positive slopes.
    d. Other: ____

8. Could some points be maximum and minimum at the same time?

    a. No. There could only be maximum points or minimum points or points that are neither of those.
    b. Yes. There could be points that, when reaching them in some directions, you have positive slopes while, when reaching them from other directions, you have negative slopes.
    c. All points along a surface have the same characteristics.
    d. Other: ____

9. If you cut a surface with a plane you could get:

    a. A point.
    b. A curve.
    c. You could not determine the shape of the figure.
    d. You do not get any figure.
    e. Other: ____

10. If you are located on a surface, how would you define the direction with higher slope?

    a. You will walk along the surface and notice the direction in which you gain height.
    b. You will walk along the surface and notice the direction in which you lose height.
    c. You will notice the direction in which you do not lose or gain height.
    d. Other: ____

11. Could surfaces you see daily could be represented as mathematical equations?

    a. No. There is no way of describing equations for surfaces in my surroundings.
    b. Yes. You could represent a surface in my surroundings through some equations.
    c. If it were possible to find equations to represent any surface, there would be more designs.
    d. Other: ____

12. In a point within a surface, how many tangent lines could you trace?

    a. Just one. Through a point in space, only one line passes.
    b. Infinite, because being at a point in space you could spin the line in any direction.
    c. It depends on the point you are studying.
    d. Other: ____

13. In a point within a surface, how many tangent planes could you trace?

    a. Infinite, because the plane could take many slopes.
    b. Just one. A plane could only have one slope at a given surface point.
    c. You cannot draw a plane tangent to a surface.
    d. Other: ____

14. The area of a finite surface is a quantity required during the design and building of structures. How can you calculate an approximate area of any type of surface?

    a. You could draw parallel lines that go through the edge of the surface so that each part of it becomes a rectangle. Then you sum those areas.
    b. You can only calculate the area of plane surfaces that are made of rectangular figures.
    c. You cannot know the area of any surface.
    d. Other: ____

15. When intercepting a plane perpendicularly with the spin axis of a rectangular cylinder, you derive:

    a. A point.
    b. A line.
    c. A circumference.
    d. Other: ____

16. Which of these tools have you used to visualize surfaces?

    a. GeoGebra®
    b. Wolfram Alpha®
    c. Desmos®
    d. Other: ____

17. Can the study and understanding of surfaces through calculus help you know your surroundings better?

    a. Yes. Calculus helps me model my surroundings.
    b. Yes. Calculus helps me determine important points along the surface.
    c. No. It is not easy to find equations that model surfaces.
    d. Other: ____

In a week, how much time do you spend playing video games?______________

Further comments:____
____

Knowledge assessment

All students who were involved in this research were asked to participate voluntarily. Their involvement in this project had merely research intentions. They were also told that they could leave the experiment at any time if they experienced motion sickness or any other discomfort.

Twenty students took part in the AR intervention. All of them were first-year students who had no previous knowledge of multivariable calculus. All of them took the pre and post-tests. The tests were graded on a scale from 1.0 to 5.0, 1.0 being the lowest score and 5.0 the highest. The scores of the students in the pretest and post-test with the knowledge change are described in Table 2.

Table 2. Variation in knowledge between the pre and post-tests

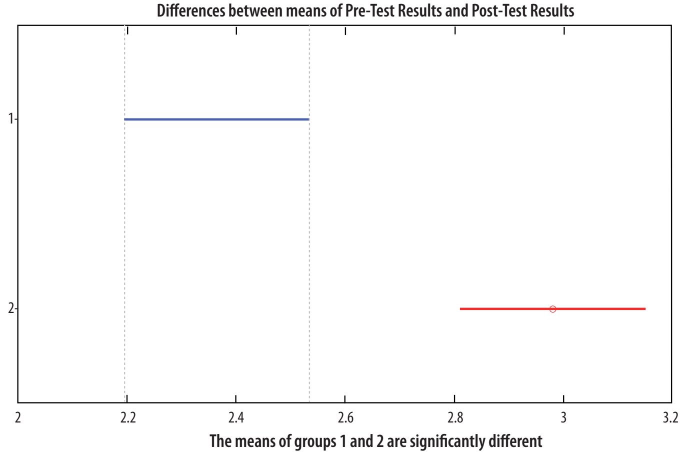
Subject	Pretest Grade	Post-test Grade	Variation
1	2.7	3.5	0.8
2	3.1	2.3	-0.8
3	2.7	2.7	0
4	2.3	3.8	1.5
5	1.9	3.1	1.2
6	3.5	2.7	-0.8
7	1.5	3.5	2.0
8	3.1	3.1	0
9	1.9	3.8	1.9
10	2.3	3.5	1.2

11	2.3	3.1	0.8
12	2.3	3.1	0.8
13	1.5	2.7	1.2
14	2.7	3.1	0.4
15	2.3	2.3	0
16	1.9	1.9	0
17	2.7	3.1	0.4
18	1.5	2.7	1.2
19	1.9	2.7	0.8
20	3.1	3.1	0

Source: Prepared by the authors

An ANOVA test showed that the means are significantly different with a p value < 0.05 ($p = 0.0007$), suggesting that means of the populations (pretest and post-test) are statistically significant. Additionally, a Tukey test was carried out to find which means were significantly different. As shown in Figure 4, the second group, in red, which is the post-test group, has a significantly higher mean than the first group.

Figure 4. Results of the Tukey Test.



Pretest described in blue and post-test in red. The results of the test show that the post-test sample has a significantly higher mean than the pretest

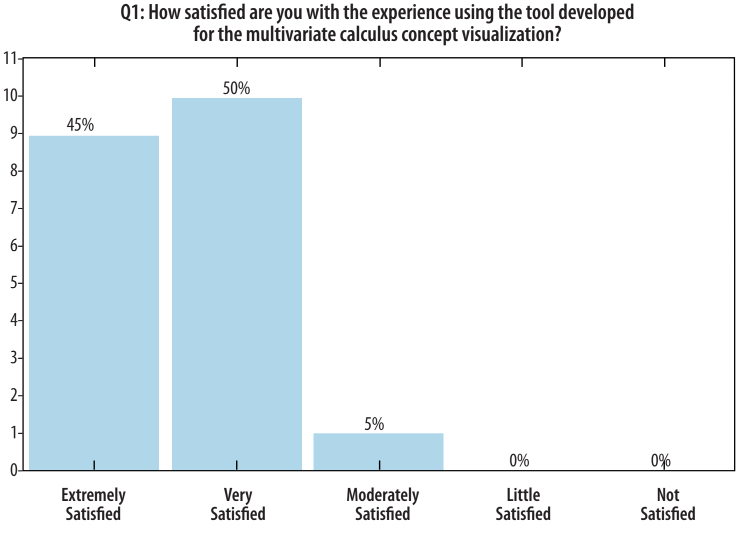
Source: Prepared by the authors

Subjective Perceptions Assessment

The main topics we wanted to assess were personal satisfaction and motivation. On the one hand, we wanted to evaluate if the users were satisfied with the tool during the experience, and, on the other, we wanted to see if their motivation increased after the AR experience.

Regarding the level of satisfaction of the students, 18 out of 20 students (90%) found the AR development satisfactory and pleasant (between Extremely Satisfied and Very Satisfied). The remaining two students did not find it as pleasant as desired (Moderately Satisfied). These results are shown in Figure 5.

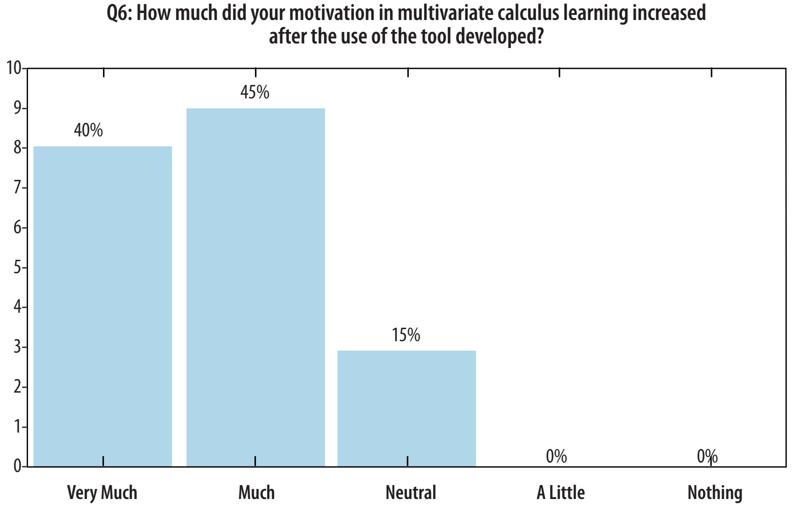
Figure 5. Students' responses regarding their satisfaction with the Augmented Reality Application



Source: Prepared by the authors

Regarding the motivation of the students in using tools for learning multivariate calculus, 19 out of 20 (95%) considered that their motivation increased after using the AR tool during the experience and only one student remained neutral, as shown in Figure 6.

Figure 6. Students' responses on the change in interest in multivariable calculus after the intervention



Source: Prepared by the authors

Conclusions and Future Work

The results of the cognitive assessment suggest that the collaborative AR application created for this project is a valuable tool that can be used in the classroom to support the instructor when introducing the intuitive knowledge underlying various multivariable calculus concepts to students who have not been exposed previously to the concepts. It is important to note that it is not the technology by itself, but the technology hand-in-hand with appropriate pedagogical guidance through the experience, inviting students to reflect about what they see in the virtual scene, that shows the potential to foster understanding in the students.

We created a very similar VR application to be used with head-mounted displays in the classroom. The AR and VR applications were used with students taking a multivariable calculus course; their pedagogical efficacy was tested, and the results were very encouraging. These results go beyond the scope of this chapter and are reported in another publication.

We are creating additional VR/AR applications to explore their use for teaching physics, with the concepts underlying parabolic motion. It will allow students to perform collaborative laboratory assignments, even if they do not share the same physical location. We also plan to design stand-alone VR/AR applications where an intelligent avatar acts as the instructor, guiding the student through a set of activities and asking them to reflect through smart self-evaluation.

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Este libro se terminó de imprimir en Artes y Letras
para la Editorial EAFIT
Medellín, diciembre de 2020
Fuente: Caslon 540 normal, *Caslon 540 italic*