

Application of Voice Personal Assistants in the Context of Smart University

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Abstract

Active methodologies based on the development of e-Learning modalities have gradually replaced traditional learning methods in recent years. This reality necessarily requires the emergence of virtual learning platforms that facilitate the creation of personalized learning and strengthen the student's motivation to learn. The use of modern voice personal assistants, based on advanced natural language understanding and machine learning techniques, is one of the resources that is showing great promise in addressing this challenge. Such resources are becoming increasingly popular because they allow users to have natural conversations without having to adhere to rigid and predefined rules.

The main objectives of this research have been to examine the current challenges of using voice personal assistants in smart universities, to better understand how this new technology could support students in their learning, and to study the influence that such resources can have on the teaching-learning process. A review of existing scientific literature on this technology and its application in educational environments, specifically in the university context, was conducted to begin addressing these challenges. Secondly, the effect that the use of this technology had on university students was studied, for which a computer application was developed using Alexa technology, analyzing the usability and satisfaction perceived by the students.

The results are presented in three research articles published in scientific journals, all of which are indexed in the first three quartiles of the Web of Science. Additionally, there is an Intellectual Property Registry for computer programs that have been filed with the Spanish Ministry of Culture, containing the application's source code (Alexa skill), and whose rights have been granted to the University of Burgos for its use. As an overall conclusion to this thesis, there is a discussion and evaluation of the results, as well as several suggestions for future lines of work.

Finally, it should be mentioned that this thesis was carried out in collaboration with the University of Burgos, under the Industrial Doctorate framework.

Keywords: chatbot, e-Learning, intelligent personal assistant, Moodle, smart university, virtual personal assistant, voice personal assistant, voice conversational agent.

Resumen

En los últimos años, los métodos de aprendizaje más tradicionales están siendo sustituidos progresivamente por metodologías activas basadas en el desarrollo en modalidades e-Learning. Este hecho genera el reto del diseño de plataformas virtuales de aprendizaje que incrementen el desarrollo de aprendizajes personalizados y que faciliten la motivación del estudiantado hacia el objeto de aprendizaje. Uno de los recursos que se está mostrando muy prometedor para abordar este desafío es la utilización de asistentes de voz modernos basados en técnicas avanzadas de comprensión del lenguaje natural y aprendizaje automático. Dichos recursos están creciendo en popularidad, permitiendo al usuario establecer conversaciones naturales sin adherirse a reglas rígidas y predefinidas.

Este trabajo de investigación ha tenido como objetivo principal el de examinar los desafíos actuales en el empleo de los asistentes de voz en el contexto de las universidades inteligentes, para comprender mejor cómo esta nueva tecnología puede ayudar a los estudiantes en su proceso de aprendizaje, además de estudiar la influencia que dichos recursos pueden tener en el proceso de enseñanza-aprendizaje. Para abordar dicho reto, en primer lugar se realizó una revisión de literatura científica existente sobre esta tecnología y su uso en entornos educativos, específicamente en el ámbito universitario, durante la última década. En segundo lugar, se estudió el efecto que el empleo de esta tecnología tenía en estudiantes universitarios para lo que se elaboró una aplicación informática utilizando la tecnología de Alexa, analizándose la usabilidad y satisfacción percibida por el estudiantado.

Los resultados se presentan en tres artículos de investigación publicados en revistas científicas indexadas en la Web of Science en los tres primeros cuartiles. Asimismo, como parte del trabajo para esta tesis, se realizó un Registro de la Propiedad Intelectual registrado en el Ministerio de Cultura de España en la categoría de programa de ordenador, cediendo los derechos de su explotación a la Universidad de Burgos. Dicho registro incluye el código fuente de la aplicación (skill de Alexa). Como conclusión general de esta tesis, se proporciona una discusión y evaluación de los resultados, así como

varias sugerencias para futuras líneas de trabajo.

Finalmente, cabe destacar que esta tesis se realizó en colaboración con la Universidad de Burgos, en la modalidad de Doctorado Industrial.

Palabras Clave: chatbot, e-Learning, asistente personal inteligente, Moodle, universidad inteligente, asistente personal virtual, asistente personal de voz, agente conversacional de voz.

Chapter 1

Introduction

Significant efforts have been made recently to adapt the educational system to the demands and expectations of the current generation of students [1]. While educational researchers have been studying the impact of computer tutoring systems on learning outcomes for more than 40 years [2], it is only over the last decade that step-based computer tutoring systems have been shown to be nearly as effective as average human tutors, and even more effective than no tutoring conditions or teacher-led classroom instruction [3].

Active learning methods have largely supplanted more traditional ones, demonstrating how e-Learning platforms are best suited for the needs of today's digital native generation of students, positioning them at the center of the educational process and empowering them to actively contribute to the whole learning process [4]. These advancements in technology are enabling constantly-growing classrooms at high schools, large-scale lectures at universities, and Learning Management Systems, making it possible to offer top-quality courses to an audience of students wider than ever before, [5, 6] with some of these technological developments aiming to improve human-machine interaction beyond traditional graphical user interfaces.

We are presently witnessing the rise of voice personal assistants with improved natural language understanding and machine learning techniques that allow users to have reasonable conversations in a natural way, without the need to follow strict, predefined commands [7]. In recent years, voice personal assistants have become increasingly influential in our daily lives, with Apple's Siri, Google Assistant, Microsoft Cortana, and Amazon Alexa among the most popular at the moment [8, 9]. They are entering the lives of millions of users and are opening new possibilities for the use of media in the context of teaching and learning, which have not been fully explored yet [10]. Likewise, they unlock a new potential to support students' learning processes across different domains due to the high degree of interactivity and

intelligence of these systems [11].

Furthermore, due to the healthcare crisis situation generated by SARS-CoV-2 (COVID-19), educators have been forced to replace in-person classes with virtual learning environments [12]. Educators need strategies and tools to construct compelling virtual learning environments that help them achieve their learning objectives, reinforcing the students' motivation for learning while improving the learning experience [13]. And so, using interactive and adaptive technologies to bring pedagogically voice-first practices into the personal home setting could be a critical step to the success of e-Learning [14].

This thesis aimed to study how voice assistant technology can help students and what kind of influence it has over their learning processes, looking at the practical application of such technology embedded within virtual learning environments already set in place and measuring the effectiveness of voice personal assistants in learning environments over the course of an extensive period of time.

However, due to the extensive magnitude of the proposed area of study, it was acknowledged that the scope of this work should be reduced. As a result, and in keeping with the previously proposed subjects for research, this work aims to examine one of the current challenges in dealing with voice personal assistants in the context of smart universities, namely, how they could provide students with a more convenient means of retrieving public site announcements and acquiring faster access to more selective information such as course announcements, grades, and upcoming due dates.

Moreover, this work required the creation of software applications that would enable the experimentation and gathering of information. Considering the substantial offering of available platforms and services to develop such applications (e.g. Google Assistant, Apple Siri, Microsoft Cortana, Amazon Alexa, Samsung Bixby, etc.) [15], it was decided from the beginning that Alexa would be the chosen technology to experiment with. Such a decision was made due to the existing familiarity with the technology since the author of this thesis holds the "AWS Certified Alexa Skill Builder – Specialty" certificate [16], issued by Amazon Web Services Training and Certification.

To that end, an extensive literature review was conducted to fully comprehend the empirical studies conducted on the subject of voice assistant technology and its application in education, with a special interest in its use in smart universities and the results obtained from such studies over the last decade. Furthermore, additional interest was given to those studies which provided guidance, recommendations, or any kind of know-how which could be later used as groundwork and best practices for the development of tools for experimentation utilizing Alexa for educational purposes.

An Alexa skill was then created, deployed, and tested on students from

various disciplines and backgrounds. Data was collected from these experiments using individual questionnaires as well as by compiling and analyzing logs from the actual usage of the Alexa skill, which provided information for a better understanding of the student's experience and guided the enhancement of the skill for further testing and experimentation.

The most important and meaningful concepts and tools used during the research work for this thesis are listed and commented on in Chapter 2 and Chapter 3. Then Chapter 4 presents the published articles with the research work done for this thesis, and additional related achievements. Finally, a discussion and evaluation of the results are available in Chapter 5 as an overall conclusion to this work, which establishes a number of proposals for future lines of work.

Chapter 2

Theoretical Concepts

2.1 Smart University

Smart University is a concept that entails the creative integration of smart technologies, features, software and hardware systems, pedagogy, curricula, learning and academic analytics, and various branches of computer science and computer engineering, to modernize all educational processes [17, 18]. The smart university concept is based on the principle of utilizing technology in all aspects of academic administration, and therefore, smart universities would implement learning and development, as well as routine administrative tasks, using cutting-edge technology and automated administrative plans [19]. Furthermore, the concept of a smart university relies on its smart components (see Figure 2.1), which use artificial intelligence systems to perform their tasks effectively and must communicate with one another to share information and experience in order to solve problems, improve the working environment, and elevate the level of students in the scientific field [20].

These are some characteristics that can be extracted and used as key indicators of the smartness associated with smart universities, divided into three categories [21]:

1. Necessary

- Effectiveness - Smart universities produce acceptable learning outcomes in contrast to traditional universities with equivalent students.
- Efficiency - Smart universities are cost-effective, with an initial capital expenditure, support and maintenance costs that are on par with traditional universities with a similar number of learners.

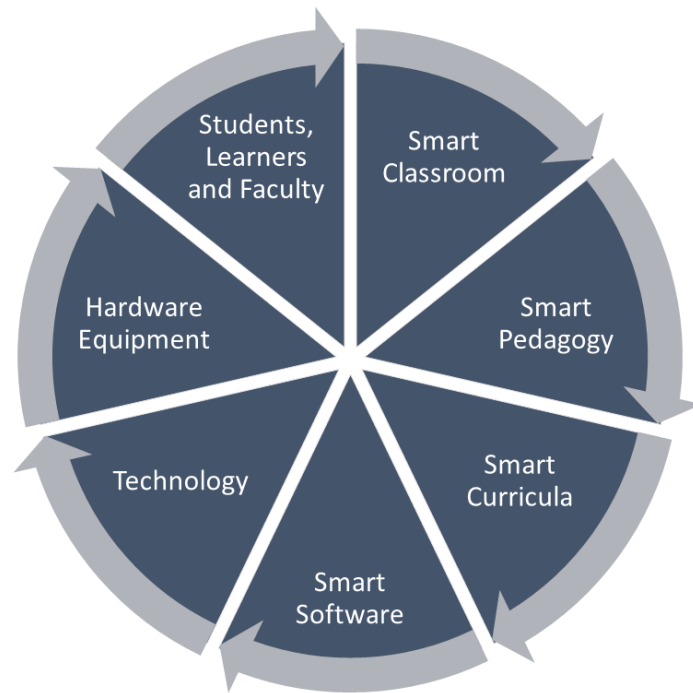


Figure 2.1: Smart university components. (Based on: [20])

- Scalable - Smart universities are effective and efficient on a large scale, spanning far beyond a single case or a small number of limited attempts.
- Autonomous - Smart universities, just as a human teacher or tutor would, can respond effectively and autonomously to a variety of learning situations and circumstances, including the capacity to help learners become more organized and attentive to their own learning goals, methods, and outcomes.

2. Highly desirable

- Engaging - Smart universities, more so than traditional universities, are capable of motivating and sustaining the interest and participation of a diverse group of students.
- Flexible - Smart universities can adjust to changes such as new students enrolling in a course, the appearance of new resources, or the addition of new objectives.
- Adaptive - Smart Universities can adapt to distinct learner needs by identifying students' skills, learning styles, and preferences.

- Personalized - Smart universities can provide tailored assignments and/or formative feedback as needed to assist both struggling and fast-paced students.

3. Likely

- Conversational - Smart universities can engage students in a conversation or promote a group discussion about a topic or issue.
- Reflective - Smart universities can provide a self-evaluation based on student progress and performance, potentially identifying activities and traits in the learning environment that can be tuned to greater effectiveness.
- Innovative - Smart universities use new and emerging technologies, as well as innovative technologies, to assist teaching and learning in contemporary ways.
- Self-organizing - Based on data that is automatically collected and used to enhance how the environment interacts with learners in different conditions, smart universities can rearrange resources and control mechanisms to improve their performance over time.

2.2 Smart Learning Environment

Smart learning environments are emerging learning environments that combine learning objects with smart and mobile technologies to deliver smart learning processes for active learning experiences (see Figure 2.2), resulting in innovative smart learning approaches, technological services to local on-campus and online students, easy local and remote student-to-faculty interactions, and local and remote student-to-student collaborations [22, 23]. In addition to providing learners with access to digital resources and interacting with learning systems in any place and at any time, smart learning environments also provide the necessary learning guidance, hints, supportive tools, and learning suggestions in the right place, at the right time, and in the right form [24].

These environments represent a paradigm shift from conventional learning techniques to new learning methods and provide student-centered learning environments that incorporate a variety of pedagogical methods and practices to exercise and reflect on the learning process in both formal and informal contexts [25].

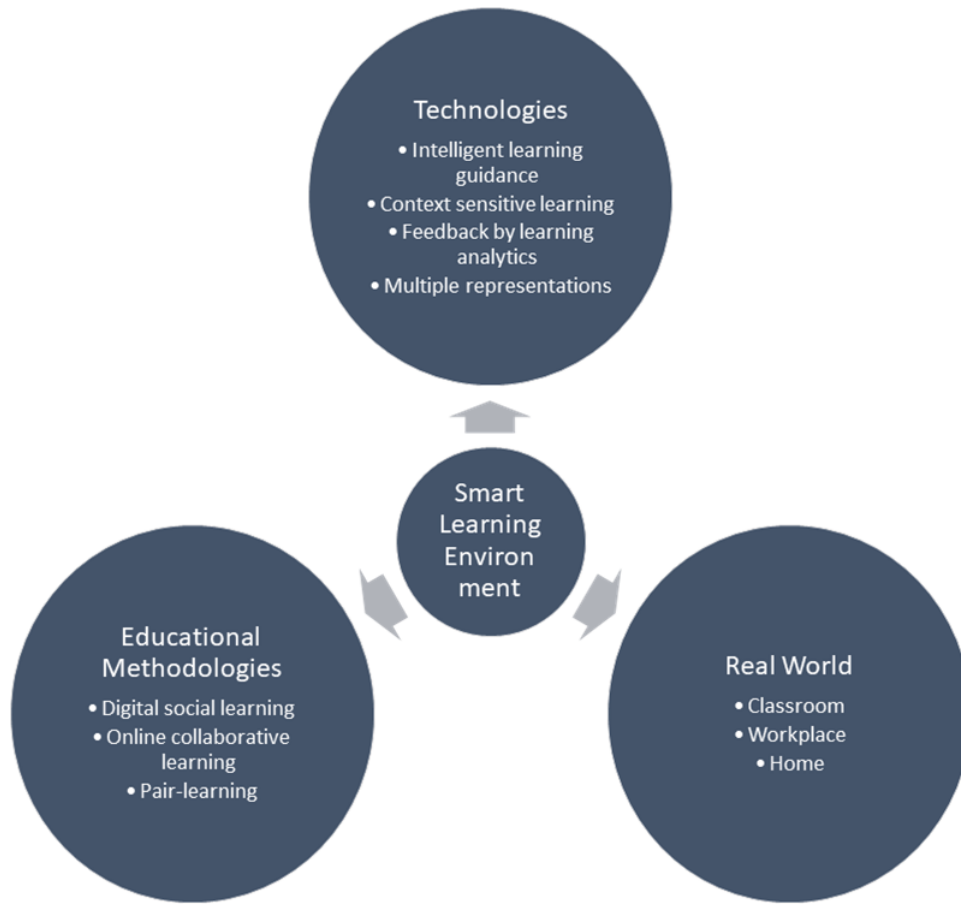


Figure 2.2: Components of a smart learning environment. (Based on: [23])

There are three key features that define a smart learning environment [26]:

- Context-awareness - Smart learning environments must provide learners with support based on their status (online or real-world).
- Adaptive support - Smart learning environments must present immediate and adaptive support based on the learners' particular needs, considering the context in which they are placed at the moment (online or real-world).
- Adaptive interface - Smart learning environments must adapt their user interface depending on the device of choice, whether this is a mobile device (such as a smartphone, tablet computer, etc.), a wearable device (such as a smart wristwatch), or an ubiquitous computing system embedded in an everyday object (such as a smart speaker, smart TV, car, etc.).

Through interaction and participation with smart learning environments, students acquire the sense of presence by experiencing the illusion of “being there”, when it could be the case that “there” does not actually exist within the particular context of the student [27, 28]. Furthermore, the effect of presence produced on a student by the proper use of a smart learning environment might potentially lead to an increase in student motivation and engagement, which in turn has a positive influence on the student’s learning [29].

2.3 From Conversational Agents to Voice Personal Assistants

Conversational agents, also known as Dialog Systems [30], are artificial computer systems designed to engage in conversation with a human user and perform tasks or provide services in response to the individual’s commands and questions [31]. These systems can process the user’s input and deliver a comprehensible output using a variety of communication methods (text, speech, imagery, gestures, and others) [32, 33]. Furthermore, voice conversational agents emulate human behavior through the integration of features like human-to-human dialog for human-machine interaction [34] and are capable of recognizing human speech, interpreting it, and responding using synthesized voices [35]. Still, modern voice conversational agents currently present usability challenges if held to the expectations set by similar systems depicted in science fiction movies [36].

In recent years, one of the most important application domains for voice conversational agents has been the development of voice personal assistants, also named in research literature as “Virtual Personal Assistants”, “Intelligent Personal Assistant”, “Voice Intelligent Personal Assistant”, or “Chatbot” [37, 38]. Some commercial examples of voice personal assistants are Apple’s Siri, Microsoft Cortana, Amazon Alexa, or Google Assistant, which are becoming increasingly influential in our daily lives [32, 39, 40]. Particularly in Spain, 10.7 percent of the population claims to already use voice personal assistants, with Apple’s Siri being the most used compared to competitors (See Figure 2.3). However, Google Assistant and Amazon Alexa seem to be the most popular in-house voice assistants (See Figure 2.4) [41].

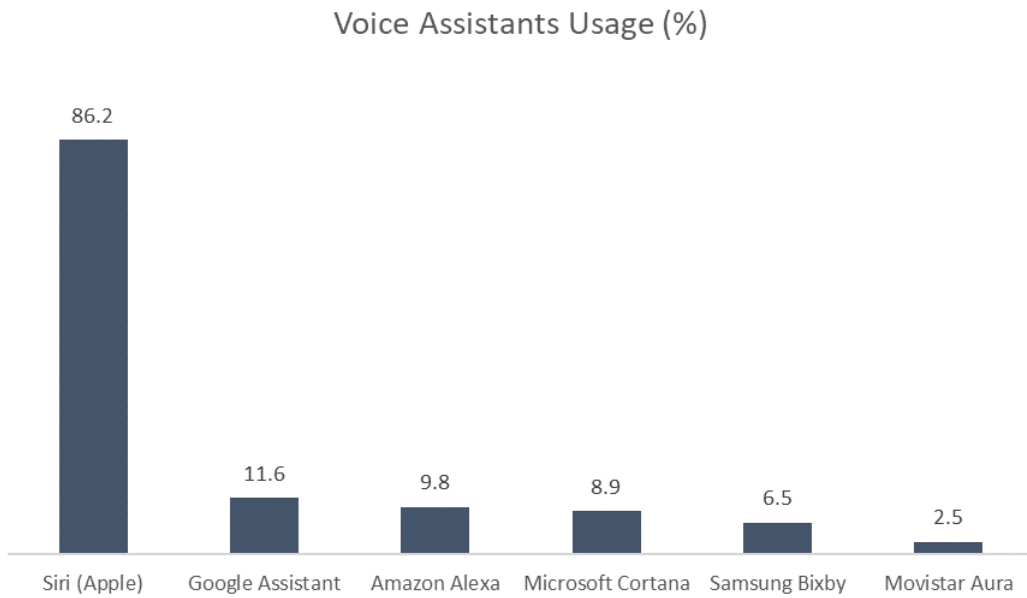


Figure 2.3: Most popular voice assistants in Spain. (Based on [41])

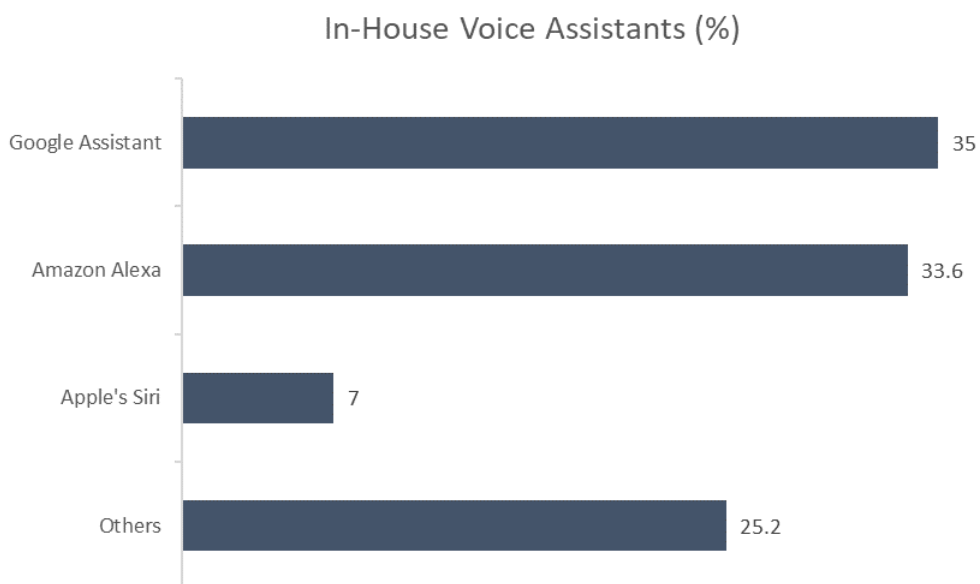


Figure 2.4: Most popular in-house voice assistants in Spain. (Based on [41])

The aim of these assistants is to support users in performing daily tasks and to meet their needs or preferences, enabling them to perform tasks spanning a broad range of scenarios, from chatting with users or shopping, to managing more simple tasks like writing an email or playing media on television [35, 42]. While the conversational capabilities of these assistants are still limited, they are proof that the tools and means already exist for replacing user-input through keyboard, mouse, and touchscreen with voice commands, using speech synthesis to guide the user through elaborated decision-making processes [43].

Nowadays, voice personal assistants are integrated into a large number of devices, such as smartphones, smart speakers, smart watches, cars, headphones, or household appliances [44], supporting quick actions through voice commands and being able to interact with the users and maintain a basic conversational flow [45] (see Figure 2.5). These devices continuously listen for the device’s activation keyword (e.g., “Alexa” or “Hey Google”) to recognize when a user makes a request and reply to that request with audible feedback and virtual or physical actions [46]. Typically, these devices integrate with the services provided by their parent companies (e.g., Amazon or Google) to process the users’ requests as well as connect with additional services from those companies that could enable access to calendar events or allow purchasing from online marketplaces.

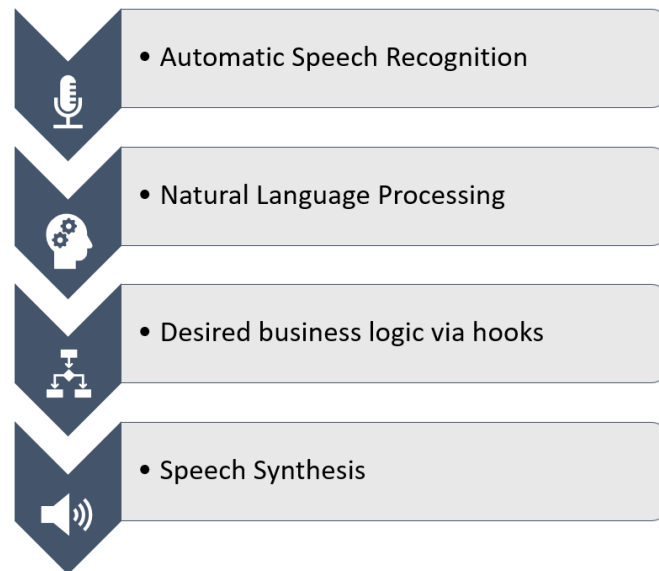


Figure 2.5: Diagram of how voice personal assistants work. (Based on [40])

Because of the cutting-edge technologies that enable voice personal assistants, as well as the universal and open nature of the internet, corporations can collect, store, process, and exploit an individual’s personal information [47]. Data privacy then becomes a major concern for technology adoption, particularly when these systems are equipped with highly sensitive microphones, which are constantly listening and mostly located within people’s private spaces [47].

Furthermore, while keyboard input or screen touch are perceived as private means for interaction with devices, voice interactivity has the potential for social embarrassment, framed by the cultural norms of public phone use, posing a hurdle to its use and acceptability [48]. As a result, engaging with voice personal assistants is commonly preferred to be done in personal spaces [48]. This reluctance to engage with voice personal assistants in public spaces could be due to a number of factors [49]:

1. To avoid attracting public attention, such as when setting a reminder to buy groceries while waiting to see the doctor, surrounded by other patients.
2. To avoid disrupting the environment, since checking game scores in a quiet room would most likely disturb the peace and calm of the room.
3. To avoid intruding into the personal space of others, as might happen when asking in a crowded elevator for directions to the nearest coffee shop.
4. To avoid verbalizing information of a private nature.

Voice personal assistants not only provide topic-specific advice and recommendations, but also detect the user’s present activities so that context-aware features can be successfully delivered and the interaction can develop. Therefore, they can be classified based on: (1) the level of intelligence of the assistant, and (2) the level of interaction [50] (see Figure 2.6).

- Interactive voice personal assistants extend the capabilities of basic assistants by enabling even further direct engagement with the user. Typically, this type of support still relies on engineers manually defining strict behavioral patterns. Unlike basic voice personal assistants, which merely provide support, interactive voice personal assistants provide aid when collaborating with users by seeking input, delivering feedback, or influencing the user during use.

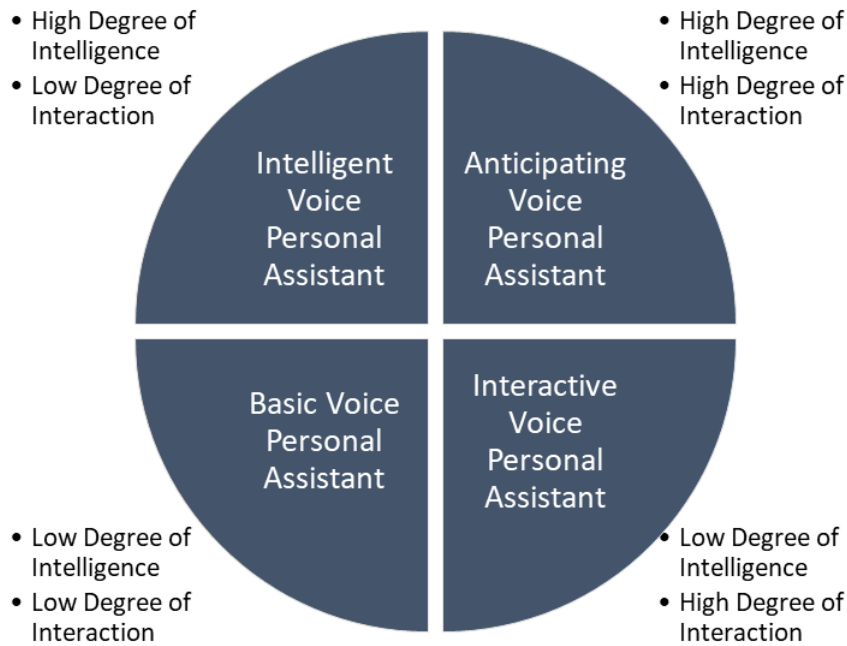


Figure 2.6: Classification of voice personal assistants (Based on: [50])

- Intelligent voice personal assistants include an intelligent component, enabling them to respond to their users and surrounding conditions. This type of assistant can adjust its assistance to the surroundings and to the preferences of particular users by collecting and analysing different types of data.
- Anticipating voice personal assistants combine a high level of intelligence and engagement with situational and context awareness to provide users with proactive support by predicting future conditions and events. The Anticipating voice personal assistants explicitly inform the user about projected results and the implications of any alternative action, and are also defined by their autonomous behavior, such as the ability to self-learn. Their assistance methods and behaviour do not remain consistent over time or become fully defined in advance. As a result, these assistants change their behavior in real time to meet the needs of their users and the context in which they operate.

Besides most modern voice personal assistants being located within the last group “Anticipating voice personal assistants”, due to their high level of intelligence and engagement combined with their situational and context awareness, they all share a set of functional principles [51]:

1. Context-awareness: context is defined as all aspects of a person's or object's physical and logical environment, which may include numerous properties that can be collected by sensors, such as location, temperature, humidity, calendar entries, or other nearby entities. As a result, a context-aware assistant can detect changes in the context and respond appropriately, to provide the user with relevant information and/or services, where relevancy is determined by the user's goal.
2. Self-evolution: unexpected effects should be managed by goal or utility models, which follow a predefined set of probable situations, and the assistant should be flexible enough to dynamically modify its behavior in response to the evaluation of how it performs if unknown context variables are recognized or known variables attain yet unknown values.
3. Multimodality: voice personal assistants can receive and/or provide information in multiple ways, using a variety of interaction behaviors such as eye motions, gestures, facial expressions, and even emotional or cognitive states, which can be implemented in a unidirectional or bidirectional mode.
4. Anthropomorphism: the degree of anthropomorphism in voice personal assistants may vary significantly depending on the user interface provided, which influences how people infer that a non-human entity has human-like features and should be treated as such. These human-like qualities make these assistants more user-friendly, but they may also lead to unrealistic expectations of their capabilities and, as a result, disappointment when those expectations are not realized.

Chapter 3

Functional Tools

3.1 Modular Object-Oriented Dynamic Learning Environment (Moodle)

Moodle is a learning system that enables educators, administrators, and students to create personalised learning environments using a single, robust, and secure system [52]. This platform offers a suite of student-centered tools and collaborative learning environments that support both teaching and learning and is available in over 120 languages [53]. Moodle is often referred to by multiple terms, such as: Course Management System (CMS), Learning Management System (LMS), Virtual Learning Environment (VLE), or Learning Content Management System (LCMS) [54].

- A virtual learning environment differs from a managed learning environment (MLE) in that it is designed to support teaching and learning rather than management. VLEs typically use web browsers to deliver instructions and assessment tools, with additional tools such as wikis, blogs, and RSS being included in more recent VLEs.
- A learning management system is a software system that allows instructors to manage and deliver online training content to students. The majority of these systems are web-based, allowing for access to learning content and administration at any time, from any location, and at any pace. Often, “LMS” and “VLE” are terms used interchangeably.
- A content management system is a data repository that can store any type of file, including documents, movies, sounds, images, and so on. CMSs are frequently used as central repositories for document storage,

control, revision, collaborative sharing, and publication. It is probably the oldest term used for software similar to Moodle.

- A learning content management system combines the capabilities of a CMS with those of an LMS. LCMSs are systems that create, store, assemble, and deliver personalized e-Learning content in the form of learning objects.

Anyone can become a professor or a learner using Moodle, and participate in collaborative learning activities such as forums, wikis, chats, workshops, and messages, which help learners create new knowledge on their own and further develop critical thinking and flexible creative problem-solving skills through mutual cooperation among members, and which can be monitored to improve the learning process [53].

3.1.1 Moodle Web Services

Moodle is comprised of the Moodle Core, which includes the learning platform's core functionality (users, courses, groups, etc.), and various subsystems that implement specialized functionality and features, including activities, repositories, filters, blogs, messaging, and tags [55]. Since Moodle 2.0, these functionalities are offered as a more structured API (Application Programming Interface), commonly known as Moodle Web Services (see Figure 3.1).

The Moodle Web Services architecture was intended to address two main issues: 1) how to deal with the fact that business logic was located at the presentation tier rather than the domain tier; and 2) how to design the architecture to support a variety of web services protocols without coupling them to the business logic [56].

The Moodle Web Services architecture is designed to be protocol agnostic, with a connector module for each supported protocol (SOAP, REST, XML-RPC, and AMF) that implements the translation of the methods implemented in the Moodle External API layer (the layer which includes each service's logic) to the appropriate protocol and syntax [57].

3.1.2 UBUVirtual

UBUVirtual is the e-Learning platform of the University of Burgos, based on the free software tool Moodle, used to provide training resources to students and methodological tools to teachers to facilitate the teaching-learning process and continuous evaluation in the European Higher Education Area,

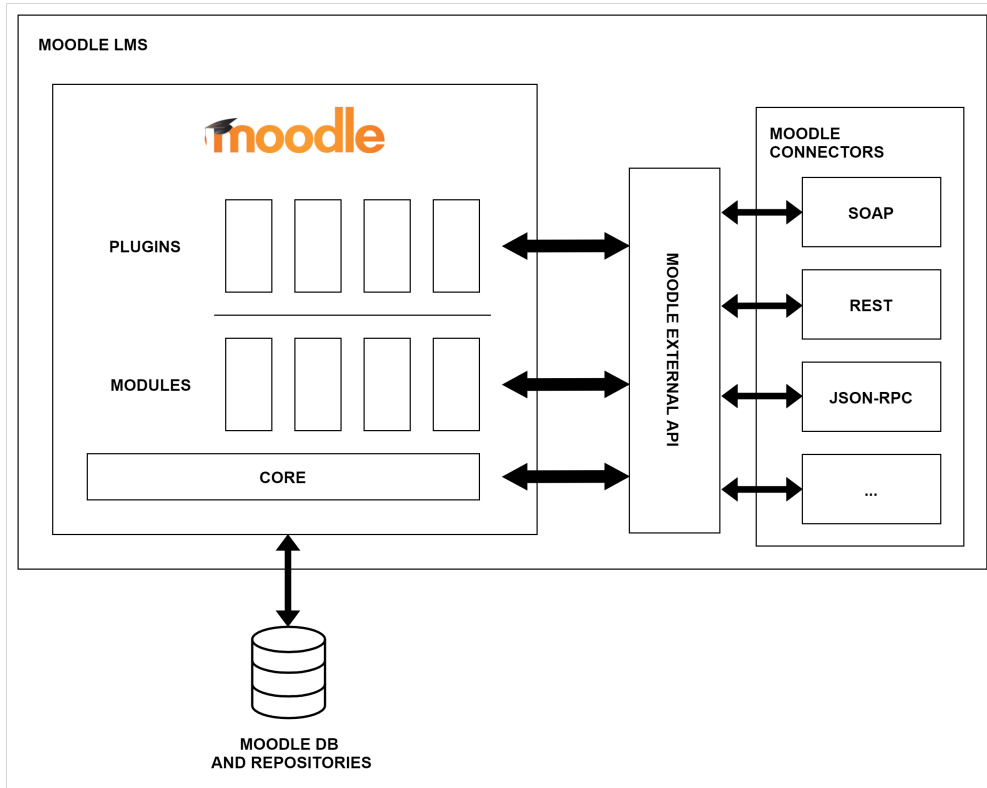


Figure 3.1: The architecture of Moodle Web Services (Based on: [55])

both for online teaching and face-to-face teaching, and adapted according to the specifications required by the university itself. Figure 3.2 presents a view of the resources and activities available on the UBUVirtual platform as of today.

Additionally, UBUVirtual stores a wide set of logs and records of the interactions that users make with the platform, including interactions with the resources and activities of the multiple courses, facilitating the subsequent analysis of usage data using different statistical and data mining techniques.

3.2 Amazon Alexa

Amazon Alexa, also known simply as Alexa, is a virtual assistant technology developed by Amazon, used in the Amazon Echo smart speaker and other devices [58]. Users can access Alexa’s built-in functionalities such as music playback, to-do lists, alarm setting, podcast streaming, audiobook playing, and others [59]. Alexa refers to these capabilities as “skills” and they are

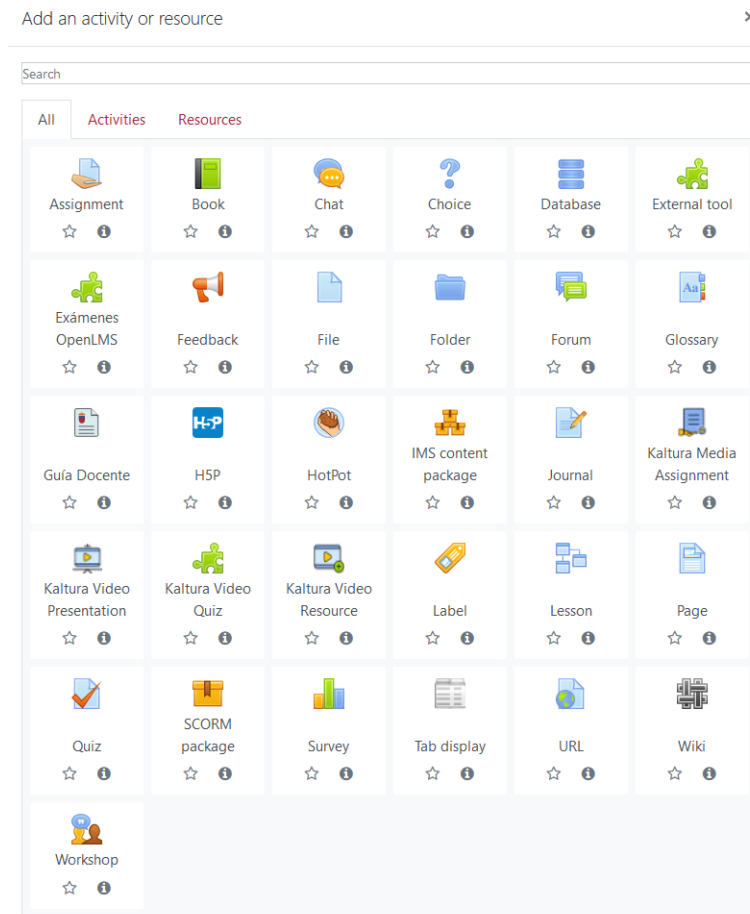


Figure 3.2: Resources and activities available at UBUVirtual.

the programmed applications that create experiences for users when they interact with their devices [60].

As shown in Figure 3.3, the Alexa architecture is made up of a number of different components, and it requires at least one Alexa-enabled device to communicate with the Alexa cloud service, either those manufactured by Amazon itself, such as the Echo series, or any other Alexa-compatible device that can communicate with the Alexa Cloud Service, which encapsulates various services for authentication, data management, and logging, as well as those services required for processing the user request, such as speech recognition, natural language understanding, and interaction modelling [59].

The term “skill” for Alexa is analogous to “application” or “app” on mobile devices [61], and although some skills are built-in and native to the Alexa platform, there are an increasing number of them developed by third parties,

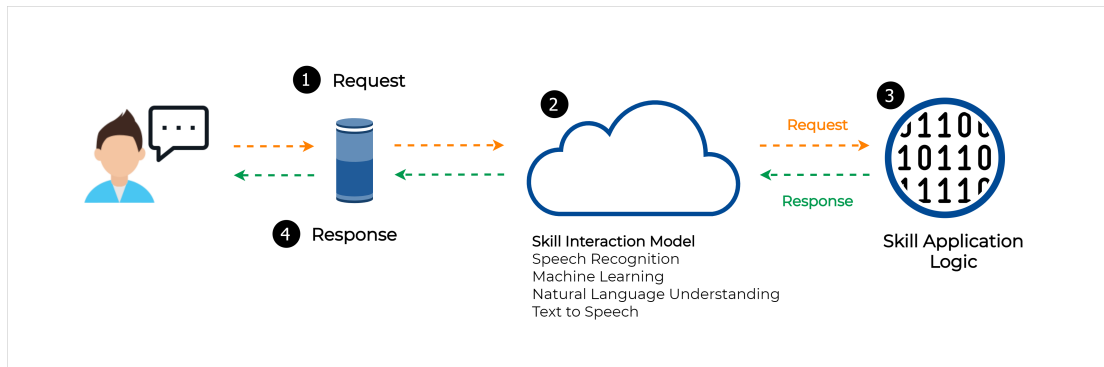


Figure 3.3: Alexa architecture

which users can install to expand the functionality of their Alexa-compatible devices [62]. Native skills are available straight from Amazon, and thus the code and dialog for those skills are fully developed by them. For example, users can ask for the time, set an alarm, or play music from Amazon Music [63]. Even so, Amazon allows third-party developers to use the Alexa Skills Kit to create Alexa skills that support a broader range of functions, allowing them to configure Alexa to communicate with their own services, run custom code, and create custom Alexa responses. Third-party skills are available on the Amazon Skill Store and cover a wide range of functions, including playing podcasts, locking doors, checking credit card balances, and telling jokes [62, 64].

By speaking the relevant invocation phrase, a user can invoke a skill, whether native or third-party [64, 65]. An invocation phrase is a combination of a skill’s invocation name and an utterance that is used to invoke a skill in response to a specific request [61, 66] (see Figure 3.4). An utterance is a word or phrase spoken by the user to invoke an intent [66, 67, 68], such as “Ask Daily Horoscopes for the Gemini horoscope”. These intents are the core functionality of any skill and are sometimes referred to as features, use cases, or user stories, and have the format “Open [invocation name] for [optional action]”, where the invocation name is frequently the skill’s name [66, 69, 70], the voice equivalent to locating the name and icon of a mobile app.

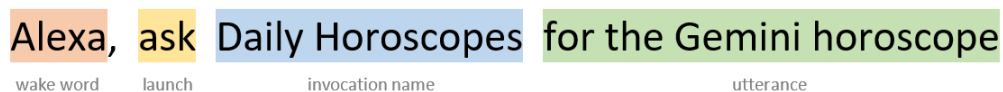


Figure 3.4: Alexa’s invocation phrase breakdown

Included within the invocation phrase could be found several connecting words (e.g., ask, open, using, from, to, about), such as the launch word, which are defined by Alexa and allow for more natural communication in the interaction [71, 72, 73]. Furthermore, a slot could also be included in the invocation phrase, defined by the intent as a list of possible arguments passed to a skill through an utterance [71, 74, 75], similar to a command-line argument or a method parameter, used by skills as spoken inputs. In the invocation phrase example above, “Gemini” is user data spoken to fill a slot in the intent utterance.

Once the user invokes a skill successfully, Alexa enters what could be defined as the skill’s context, and from that moment on, it will only accept voice commands predefined by the skill, along with some built-in intents already available, such as “Cancel”, “Help”, “Stop”, and “Fallback”, which allow users to ask the skill for help or leave the skill’s context, for example.

3.2.1 Privacy and Security Concerns

Although smart speakers have a multitude of compelling capabilities, they also have a number of privacy and security risks, which are significant barriers to voice personal assistant adoption and use [76, 77, 78]. Many studies and press reports have shown smart speaker vulnerabilities such as weak voice authentication [79, 80] or continuous listening and recording [81]. Furthermore, Alexa’s recently added features (calling and messaging) have sparked plenty of security and privacy worries among consumers.

When switched on, smart speakers remain in a constant listening state, waiting for a predetermined “wake-word” to activate them and allow them to interact with the user. This “always on” mentality raises privacy concerns for users because activating the smart speaker also starts a transfer of live audio data through WiFi for processing and storage [82].

Furthermore, it has been demonstrated that voice commands that are unintelligible to human listeners can control devices with voice interfaces [83], and similarly, speech recognition systems can be fooled into receiving and responding to voice commands that humans cannot understand using the high-frequency dolphin attack [84]. Device hacking, recording of private conversations, 24/7 listening activities, the collection, sharing, and storage of private data, and the “creepy” nature of the devices are all among the privacy and security concerns raised by users in studies [85, 86].

Information about how voice assistant devices address privacy and data management is generally kept in long document-style pages on websites. However, it is questionable the impact these guides have and whether the presentation style might hinder users’ efforts to understand how their in-

formation is being processed and used [87, 88]. Moreover, according to the latest research on older individuals’ use of voice personal assistants, they have similar privacy concerns but are less tolerant of privacy breaches than other groups surveyed, leading them to abandon the use of their devices [87].

Particularly in the case of Alexa, two new features were added recently in response to such privacy concerns [89, 90]: 1) Using the Alexa mobile app, users can review their voice interaction history and delete any previous recordings; 2) users can also enable the “deletion by voice function” which will immediately render user utterances “off the record” by providing voice commands like “Alexa, delete what I just said” and “Alexa, delete everything I said today”.

Providing an opportunity to delete their voice recordings can empower users, leading to some relief from unwanted data sharing [91, 92]. On the other hand, it is possible that users will not endorse such features as an attempt to completely eliminate privacy concerns [46], but rather see them as part of Amazon’s public relations campaign. Therefore, the availability of features for voice recording deletion may exacerbate the tension between security concerns and the convenience provided by personalized online services, given that smart speakers require continuous audio data collection in order to function efficiently and provide better user-tailored services [93].

Chapter 4

Publications and Achievements

This chapter presents three main publications, merits of this doctoral thesis, all of which are indexed in the *Web of Science* (WOS) citation database and published in journals with high visibility and rank. In addition to those publications, the source code for the Alexa skill used for experimentation during this research was registered with the Intellectual Property Registry in Burgos (Spain). Finally, note that this thesis was carried out in collaboration with the University of Burgos under the Industrial Doctorate framework.

4.1 Article 1: *Effectiveness of Using Voice Assistants in Learning: A Study at the Time of COVID-19*

This article is available at the *International Journal of Environmental Research and Public Health* (ISSN 1660–4601), an interdisciplinary, peer-reviewed, open-access journal published semimonthly online by MDPI. It covers Environmental Sciences and Engineering, Public Health, Environmental Health, Occupational Hygiene, Health Economic and Global Health Research, etc. It is an open-access journal, free for readers, with article processing charges (APC) paid by authors or their institutions, and it is indexed within Scopus, SCIE, and SSCI (Web of Science), PubMed, MEDLINE, PMC, Embase, GEOBASE, CAPus / SciFinder, and many other databases, with a rapid publication process where manuscripts are peer-reviewed and a first decision is provided to authors approximately 17.8 days after submission, with acceptance to publication undertaken in 3.6 days.

The *International Journal of Environmental Research and Public Health* can be found on the Journal Citation Report database, within the category *PUBLIC, ENVIRONMENTAL & OCCUPATIONAL HEALTH - SSCI*, listed in the first quartile, based on its Journal Impact Factor (JIF) (Q1 JIF = 76.42). At the time the paper was published, the journal ranked 42th out of 176 with a Journal Impact Factor (JIF) of 3.390 and a Journal Impact Factor Without Self Citations of 2.819 (See Figure 4.1).

Regarding the current status of the article, and based on metric data from *Web of Science*, the paper has 12 citations and 66 references (see Figure 4.2). As well, from the journal's metric data, it can be found that the article has had 2577 views of its abstract and 2165 views of the full document since the date of publication (See Figure 4.3).

Publishing Date: August 4th, 2020

Journal Name: International Journal of Environmental Research and Public Health (ISSN 1660–4601)

Journal Rank: Q1

Impact Factor: 3.390 (2020); 5-Year Impact Factor: 3.789 (2020)

Link: <https://doi.org/10.3390/ijerph17155618>

Journal Impact Factor Trend 2020

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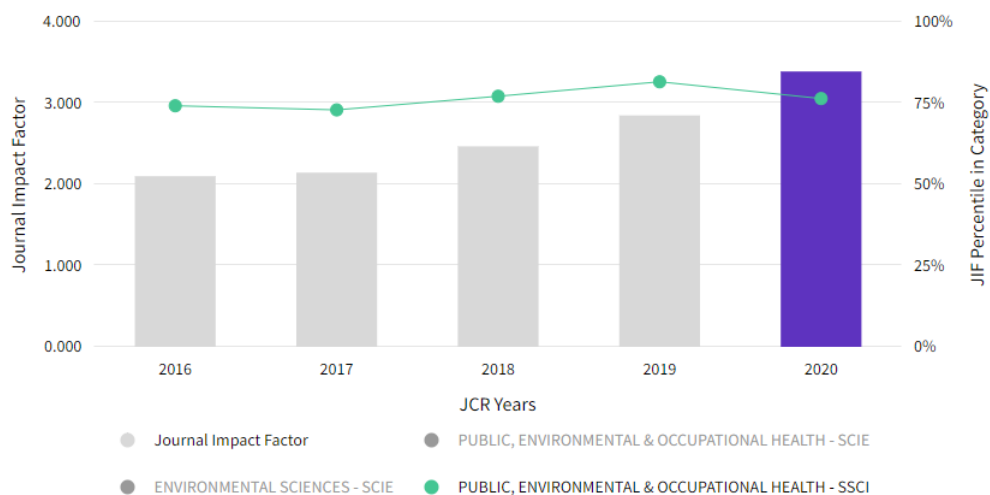


Figure 4.1: Article 1 - Journal Impact Factor 2020. (Source: [94])

Effectiveness of Using Voice Assistants in Learning: A Study at the Time of COVID-19

By: Saiz-Manzanares, MC (Consuelo Saiz-Manzanares, Maria) ¹; Marticorena-Sanchez, R (Marticorena-Sanchez, Raul) ²; Ochoa-Orihuel, J (Ochoa-Orihuel, Javier) ²
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Abstract

The use of advanced learning technologies in a learning management system (LMS) can greatly assist learning processes, especially when used in university environments, as they promote the development of Self-Regulated learning, which increases academic performance and student satisfaction towards personal learning. One of the most innovative resources that an LMS may have is an Intelligent Personal Assistant (IPA). We worked with a sample of 109 third-grade students following Health Sciences degrees. The aims were: (1) to verify whether there will be significant differences in student access to the LMS, depending on use versus non-use of an IPA. (2) To verify whether there will be significant differences in student learning outcomes depending on use versus non-use of an IPA. (3) To verify whether there will be significant differences for student satisfaction with teaching during the COVID-19 pandemic, depending on use versus non-use of an IPA. (4) To analyze student perceptions of the usefulness of an IPA in the LMS. We found greater functionality in access to the LMS and satisfaction with teaching, especially during the health crisis, in the group of students who had used an IPA. However, both the expansion of available information and the usability of the features embedded in an IPA are still challenging issues.

Keywords

Author Keywords: advanced learning technologies; intelligent personal assistant; blended learning; COVID-19

Keywords Plus: STUDENTS; TECHNOLOGIES; ACHIEVEMENT; BEHAVIOR

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Figure 4.2: Article 1 - Record from the Web of Science. (Source: [95])

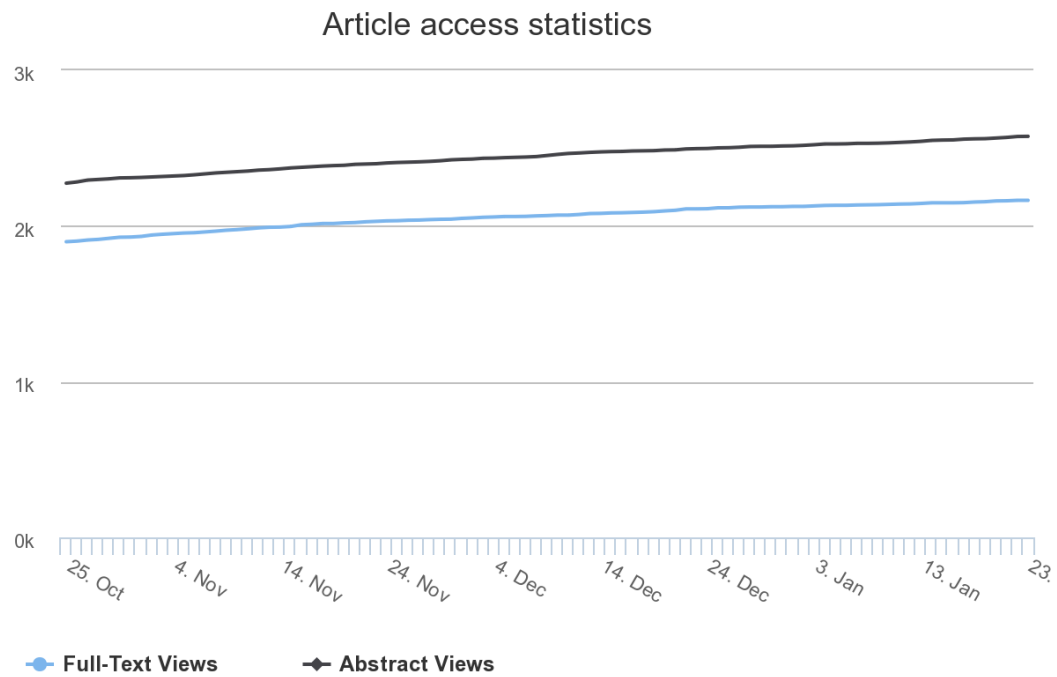


Figure 4.3: Article 1 - Access Statistics. (Source: [12])



Article

Effectiveness of Using Voice Assistants in Learning: A Study at the Time of COVID-19

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Abstract: The use of advanced learning technologies in a learning management system (LMS) can greatly assist learning processes, especially when used in university environments, as they promote the development of Self-Regulated learning, which increases academic performance and student satisfaction towards personal learning. One of the most innovative resources that an LMS may have is an Intelligent Personal Assistant (IPA). We worked with a sample of 109 third-grade students following Health Sciences degrees. The aims were: (1) to verify whether there will be significant differences in student access to the LMS, depending on use versus non-use of an IPA. (2) To verify whether there will be significant differences in student learning outcomes depending on use versus non-use of an IPA. (3) To verify whether there will be significant differences for student satisfaction with teaching during the COVID-19 pandemic, depending on use versus non-use of an IPA. (4) To analyze student perceptions of the usefulness of an IPA in the LMS. We found greater functionality in access to the LMS and satisfaction with teaching, especially during the health crisis, in the group of students who had used an IPA. However, both the expansion of available information and the usability of the features embedded in an IPA are still challenging issues.

Keywords: advanced learning technologies; intelligent personal assistant; blended learning; COVID-19

1. Introduction

1.1. Self-Regulation Learning and Advanced Learning Technologies

The use of advanced learning technologies can be an excellent teaching aid for efficient learning processes, especially when adapted to Self-Regulated learning (SRL). The learner can use various technologies to interpret how to approach the resolution of learning tasks and, according to the needs that are detected, the use of a particular learning technology will help to guide the learner towards successful outcomes [1]. Advanced learning technologies are frequently applied within a Learning Management System (LMS). An LMS has many advantages, among which we can highlight personalized attention to the student [2], which makes it possible to increase motivation [3]. Likewise, an LMS can facilitate individual and group work [4], and the use of different resources such as virtual laboratories, computer graphics, flipped learning, and flipped classroom experiences, virtual workshops, and messaging, among others [5]. The use of advanced learning technologies can also facilitate collaborative work within an LMS, such as the application of the Project-Based learning (PBL) methodology [6,7]. Therefore, it can be used for the analysis of multimodal and multichannel

data on SRL provided by LMS environments, in which different resources such as smart tutoring, serious games, multimedia resources, augmented reality resources, and virtual reality are applied. In addition, LMS with additional technologies can be used to record information related to eye tracking, physiological records, facial expressions, and speech analysis, among others [8–11]. Later, these records can be analyzed with statistical and data-mining techniques, through which the learning path of an individual student or a group of students may be consulted during the resolution of different tasks [12]. In addition, the use of LMS with additional technologies can facilitate the use of SRL in almost real time [8]. The collaborative methodology implemented through LMS with additional technologies will guide student learning processes and provide oriented feedback to processes [13]. This methodology is useful through automated and individualized resources, so that the help each student may need is available at any time [14]. Nevertheless, learning autonomy with an LMS is a related disadvantage, due to the need for continuous supervision of the LMS by the teacher. However, improvements to the usability of LMSs have been advanced in recent research by the introduction of intelligent multi-agents, currently found in many automated chat systems. Based on natural voice assistance, these systems can perform many internal and external actions based on the user search queries. The results show that the proposed system can have a positive impact on both students' perceptions of the usability of an LMS, and student performance [15].

1.2. Advanced Learning Technologies and Intelligent Personal Assistant

The use of an Intelligent Personal Assistant (IPA) to improve learning is an emerging practice that, although not yet widespread, has an important future role. The implementation of IPAs through Voice User Interfaces (VUIs) (see Barcelos et al. [16] for an analysis of the taxonomy of voice assistants) means that these assistants can give immediate and intuitive responses to natural language stimuli, so that the user can develop voice interaction through the computer system. In addition, many of them include the possibility of creating applications at no cost for their development and use, such as the Amazon Echo or the Google Home assistants. The system begins from a stimulus (voice) and gives an answer to the query from the user. The characteristics of these IPAs are their functionality, immediate availability or inductiveness, and the empathy they generate with the user, and some are compatible with the Chatbot format [17]. Recent studies have indicated that IPAs can increase their efficiency, if they include the figure of an avatar as an agent of conversational interaction [12]. In educational contexts, IPAs are incorporated in LMSs, such as Moodle (Modular Object-Oriented Dynamic Learning Environment), specifically for the support of learning among students with some type of educational need [18], such as the visually impaired. The functionality offered by IPAs includes guidance for navigation on the platform or on the web [15], guidance for both reading and writing texts [19], and providing feedback on the tests results, for example, quizzes [18]. IPAs are also incorporated in Moodle modules, one example of which is the "Lesson". Bearing IPA architecture in mind, it can be a tool to build scripts and learning scenarios [17]. This new IPA functionality is potentially effective in virtual labs and simulated environments, as well as when completing quizzes [20]. The incorporation in Moodle of a module called "voicerec" [21] also recently commenced, although this technology is still in an initial state of development and presents implementation difficulties. Its advantages for the user are that it favors coaching and helps the student to find and to access information that has been tested, filtered, and prepared by the teacher. It can also be used at all times, which favors the personalization of learning and, at the same time, promotes collaborative work (teacher-student, student-teacher, student-student, student-materials, etc.). All of these aspects increase student motivation for learning [22].

Regarding the studies on the usability assessment of IPAs, users have indicated that interfaces must be adapted to the needs of each task [23,24]. IPAs that include holograms are under evaluation as learning aids [25,26]. In summary, the type of IPA and its objectives vary and although they are all implemented using natural language, the technology underlying each one is different [27]. In short, IPAs are increasingly finding their way into educational and health-related environments [28,29]. Their advantages are that they encourage personalization in learning [30,31] and in therapeutic

intervention [15]. In addition, they can provide insight into patterns of interaction, on which basis students can be provided with personalized interventions [32,33]. Even so, this technology is very complex and is still in an initial state of development [28]. Research studies therefore have emphasized the need for extensive research in this area [34,35].

1.3. The Use of Voice Assistants: Applicability in Prevention of Learning Difficulties

As previously noted, current IPA technology incorporates Machine Learning techniques (deep learning and reinforcement learning) resources based on voice-recognition systems [36]. IPAs provide users with information on coursework, facilitating its planning [37,38]. Specifically, the recent use of this technology in university-learning contexts has been associated with very good results and levels of acceptance, specifically among students with special educational needs (visual, auditory, memory, etc.) [39,40]. Furthermore, computer security resources are also incorporated in IPAs, as users must log in before implementing them [41]. Their inclusion in blended learning university learning environments is also beginning to find acceptance, increasing their functional applications [42,43]. IPAs also generate high levels of student satisfaction, as students can access teaching at the most convenient time and place and can receive personalized feedback [44]. The use of this technology also provides a further channel for teachers and academic leaders to connect with students and to understand their main concerns [45]. IPAs can likewise be used to provide students with information on administrative aspects [45,46] and they are very useful for students with visual [47] and auditory needs [48]. These users particularly value the versatility of access to information searches [49]. However, recent studies have also indicated that each IPA needs to be adapted, in terms of both interface and functionality, to respond to the needs of each user [50–52]. This field of study still has a long road to travel down, as users currently value the effectiveness of IPAs at only 60% [53].

In conclusion, the world is increasingly turning digital, which implies an urgent need for a series of changes to teaching methods for the inclusion of learning tools within higher education. Experts are calling for an intelligent university in which technology and pedagogy are implemented in teaching–learning environments [54,55]. These environments may be blended learning, or virtual, yet they are quite unlikely ever to be purely face-to-face again. In particular, the global pandemic caused by COVID-19 has quite suddenly underlined the value of telematic teaching tools, prompting governments and university leaders to urge both teachers and students to make good use of these technologies. Research must therefore be conducted to determine the effectiveness of these different resources such as IPAs in blended learning and e-learning spaces [5,56,57].

Based on the research noted above, the research questions in this study are as follows: (RQ1) to verify whether there will be significant differences in student access to the LMS, depending on use versus non-use of an IPA; (RQ2) to verify whether there will be significant differences in student learning outcomes depending on use versus non-use of an IPA; (RQ3) to verify whether there will be significant differences for student satisfaction with teaching during the COVID-19 pandemic, depending on use versus non-use of an IPA; (RQ4) to contrast students' perceptions of the usefulness of an LMS that incorporates an IPA.

2. Materials and Methods

2.1. Participants

The convenience sampling process concluded with a sample of 109 third-grade students in Health Sciences degrees: 61 in Group 1 and 48 in Group 2. The sample included all students studying on the third year of a Health Sciences degree at the University of Burgos. In Table 1, the statistics on the two variables, age and sex, can be consulted in Table 1.

Table 1. Description of the sample and the variables: gender and age.

Participant Type	Gender						
	N	n	Men		n	Woman	
			Mage	SDage		Mage	SDage
Group 1 (Nursing Degree)	61	5	21.40	0.90	56	23.54	6.30
Group 2 (Occupational Therapy Degree)	48	7	21.71	1.90	41	22.37	2.19
Total	109	12	21.58	1.50	97	23.04	5.01

Note. Mage = Mean age; SDage = Standard Deviation age.

2.2. Instruments

(a) *The Scale of learning strategies (ACRAR)* by Román and Poggioli [58]: a widely tested instrument in investigations on learning strategies. It is used to identify 32 strategies at different times of processing information: acquisition information ($\alpha = 0.78$); encoding information ($\alpha = 0.92$); recovery information ($\alpha = 0.83$); and metacognition strategies ($\alpha = 0.90$). In this study, only the metacognitive strategies scale was used. The indicators of scale validity for the sample were metacognition strategies $\alpha = 0.90$. ACRAR has been widely validated among secondary education and university students [59].

(b) *Alexa's Computer application. "UBU(Universidad de Burgos) VoiceAssistant"*: a specific application was developed for students to consult the key dates on the course (delivery of practices, completion of questionnaires, delivery of project, etc.) through a (mobile or computer) device. This application has a client-server within the Alexa service system integrated in the Amazon Web Service (AWS). An example of the interface and operation can be seen in Figures 1 and 2, respectively. Students have first to accredit their identity to enable use of the "UBUVoiceAssistant" computer application. This process is achieved with the use of UBUVirtual, the learning platform (LMS) of the University of Burgos. The students must provide valid credentials in the accreditation of their identity to access the platform. After the successful validation of these credentials, the student is then allowed further access to the "UBUVoiceAssistant" Computer application. The connection is therefore secure, and the protection of personal data is guaranteed [60].

**Figure 1.** Intelligent personal assistant (IPA). Skill Alexa "UBUVoiceAssistant".

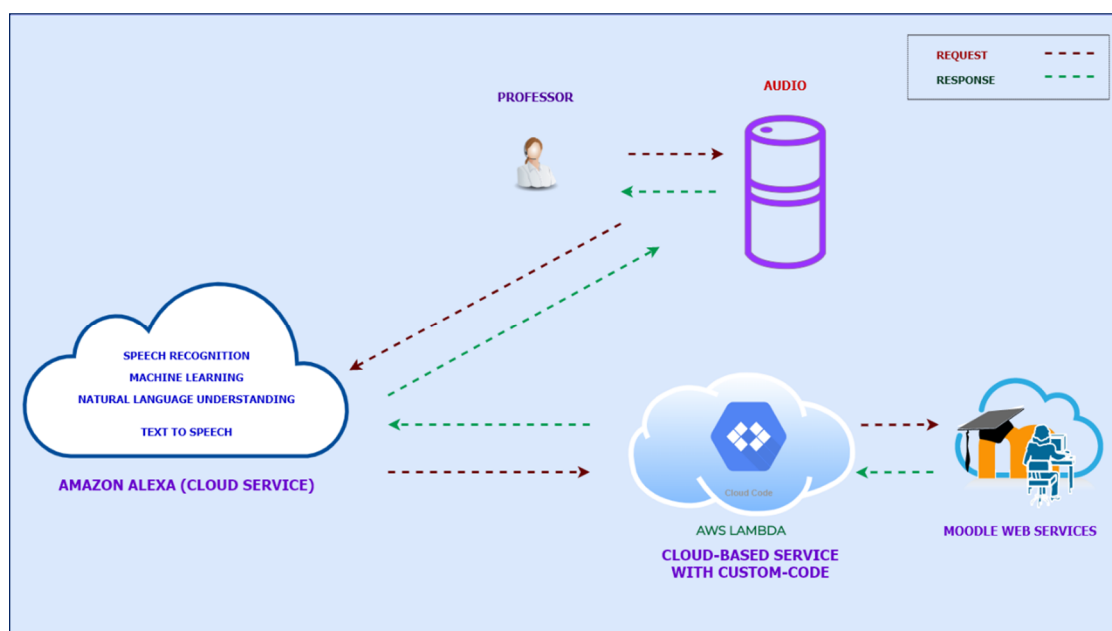


Figure 2. Diagram of the operation of the “UBUVoiceAssistant” application from Moodle.

(c) *Scale of assessment of the development of the subject.* The ad hoc development of the scale yielded 18 closed response questions, measured on a 5-point Likert-type scale, and 8 open-ended questions (4 of which refer to the development of teaching during the COVID-19 health crisis) [20]. The total reliability of the scale was $\alpha = 0.95$ and, for each item, the values were within an interval of $\alpha = 0.94$ – $\alpha = 0.96$. The scale can be found in the Supplementary Material, Table S1.

(d) *Questionnaire for assessing the functionality of the IPA “UBUVoiceAssistant”.* This instrument consists of two closed-ended questions: a multiple-choice question (with 5 options) a no/yes question, and three open-ended questions. As it is fundamentally a qualitative opinion survey, no reliability analysis could be performed. The questionnaire can be consulted in the Supplementary Material, Table S2.

(e) *Learning Management System “UbuVirtual” based on Moodle 3.7:* UBUVirtual was used in Moodle version 3.7 with a platform design based on a constructivist development designed for personalized learning and collaborative work on the platform [61–63].

(f) *eOrientation plugin:* a Moodle plugin, now registered under patent No. BU-09-20, was funded through research project No. BU032G19 awarded for research, in 2019, by the Junta de Castilla y León [64]. The plugin is compatible with Moodle log analysis of student and teacher access to the platform, and interaction with it through the various available activities and resources [65]. This Moodle plugin and its associated graphics can be used to follow the progress of students, for more information see the research of Sáiz-Manzanares, Marticorena-Sánchez, and García-Osorio [65].

(g) *Pedagogical Model:* in both groups, the same pedagogical model was used. The pedagogical model includes the following elements: development and defense of PBL, quiz-type questionnaires, and co-evaluation activities in evaluation processes throughout the teaching–learning process and flipped learning experiences. The effectiveness of this pedagogical model has been tested in various investigative studies [5,6,25,35,56,61,63,65].

2.3. Procedure

Before the study commenced, the authorization of the Bioethics Committee of the University of Burgos and the informed consent of all participants were obtained in writing (see point 2.5). The subject was designed with a blended learning methodology using flipped classroom experiences, which meant that teaching, although delivered in person, was through a Moodle-based LMS (UBUVirtual: learning

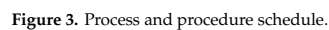
platform of the University of Burgos), which contained hypermedia resources (videos in flipped classroom experiences and computer graphics). The pedagogical design of the subjects included the following elements: practices (weighted 20% of final grade), quizzes (weighted 30% of final grade), project work, and a defense of a project using practical assumptions drawn from PBL methodology (weighted 25% and 20% of final grade, respectively) and participation in co-evaluation (satisfaction and opinion surveys on the organization of the course) (weighted 5% of final grade). The difference between Group 1 and Group 2 was that, in the second group, an IPA based on the Alexa computer application and integrated into AWS was used from the beginning of the course. Students accessed the IPA using their UBUVirtual credentials. The voice assistant informed the students about events and test deliveries and evaluation procedures in relation to course planning. These events were also collected in a PDF calendar of processes and procedures with assignment dates, available to students from the beginning of the course (an example can be seen in Figure 3). The development of the teaching began on February 3 and ended on April 2 (9 weeks) of 2020. However, on March 12, the Spanish state declared a state of alarm over the COVID-19 health crisis and from that time onwards the teaching was imparted online, exclusively for both groups, over a total period of 4 weeks.

2.4. Design and Data Analysis

A quasi-experimental design with an equivalent control and sample group was used for quantitative data analysis. With regard to statistical analyses, the non-parametric Mann–Whitney U test for independent samples was used to check homogeneity between groups before the intervention. Asymmetry and kurtosis analyses were also used to study the normality of the sample. In addition, to check research questions 1, 2 and 3, a single factor fixed-effects ANOVA and the eta-squared formula yielded their respective effect sizes. In addition, a descriptive multidimensional ideographic design was used for the qualitative analysis. The open-ended responses to research questions 3 and 4 were analyzed, first through a categorization of the responses, and then through a frequency and percentage analysis applied to their categorizations. The SPSS v.24 software has been used for data analysis [66].

2.5. Ethical Approval

At the beginning of the project, approval was obtained from the Bioethics Committee of the University of Burgos (No. IR 30/2019). The informed written consent of all participants in the study was documented in accordance with the Declaration of Helsinki.



3. Results

3.1. Previous Statistical Analyses

Before the study began, an analysis of the homogeneity between groups was performed with the ACRAr Metacognitive Strategies Scale [58,59], using the non-parametric Mann–Whitney U test for independent samples, of the responses from the students before the instruction commenced. As can be seen in Appendix A, no significant differences are found in Table A1. Therefore, the groups can be considered similar.

A normality analysis was then performed on the sample distribution on the ACRAr Metacognitive Strategies Scale [58]. Values over |2.00| are indicative of extreme asymmetry and the lower values that the sample follows are indicative of a normal distribution. Kurtosis values between |8| and |20| suggest extreme kurtosis. In this study, as can be seen in Appendix A, no extreme values of asymmetry or kurtosis were detected, so it was concluded that the sample followed a normal distribution, and parametric statistics may be applied.

3.2. Research Question 1

A fixed-effect factor ANOVA was performed (IPA use vs. non-use) to test RQ1. As can be seen from Table 2, significant differences were found for: the number of accesses to the practice resources on the platform in favor of Group 2, for which IPAs returned a high effect size of 43% [$F_{(1,107)} = 81.97$, $p = 0.00$, $\eta^2 = 0.43$]; access to information on the quiz-tests [$F_{(1,107)} = 116.25$, $p = 0.00$, $\eta^2 = 0.52$] in favor of Group 1 that made no use of an IPA, with a high effect size of 52%; and, access to all information on the platform [$F_{(1,107)} = 21.81$, $p = 0.00$, $\eta^2 = 0.17$] in favor of Group 1 that had made no use of an IPA, with a low effect size of 17%.

Table 2. A single factor fixed-effects ANOVA (IPA use vs. non-use).

	G1 N = 61	G2 N = 48	$F_{(1,107)}$	p	η^2
	M (SD)	M (SD)			
Access to practical information	11.48(4.21)	68.85(4.74)	81.97	0.00 *	0.43
Access to information on the quiz-tests	211.48(8.30)	76.71(9.35)	116.25	0.00 *	0.52
Access to project information	30.11(2.72)	30.12(3.07)	0.00	0.99	0.00
Access to co-evaluation information	26.64(2.37)	21.30(2.67)	2.30	0.13	0.02
Access to total information	279.71(11.77)	196.92(13.26)	21.81	0.00 *	0.17

* $p < 0.05$. Note: N = number of participants; M = Mean; SD = Standard Deviation; η^2 = eta squared (effect size); G1 = Use de IPA; G2 = No use of IPA.

3.3. Research Question 2

In relation to RQ2, significant differences were only found in favor of Group 1 for the learning outcomes obtained in the practices [$F_{(1,107)} = 6.02$, $p = 0.02$, $\eta^2 = 0.06$] with a very low effect size (Table 3).

Table 3. Single factor fixed-effects ANOVA (IPA use vs. non-use).

	G1 N = 60	G2 N = 45	$F_{(1,32)}$	p	η^2
	$M (SD)$	$M (SD)$			
Learning outcomes in practices	1.99(0.04)	1.96(0.10)	6.02	0.02 *	0.06
Learning outcomes in questionnaires	2.53(0.38)	2.61(0.46)	1.14	0.29	0.01
Learning outcomes in project development	2.17(0.24)	2.14(0.37)	0.35	0.55	0.003
Learning outcomes in defence project	1.82(0.10)	1.85(0.30)	0.60	0.44	0.01
Learning outcomes in co-evaluation	0.19(0.14)	0.19(0.14)	0.01	0.94	0.00
Learning outcomes Total	8.70(0.56)	8.70(1.17)	0.00	0.99	0.00

* $p < 0.05$. Note: N = number of participants; M = mean; SD = standard deviation; η^2 = eta squared (effect size); G1 = IPA use; G2 = IPA non-use. One participant in Group 1 and 3 participants in Group 2 never completed the course.

3.4. Research Question 3

The tests performed on RQ3 may be checked in Appendix A. The results indicate that the degree of student satisfaction with the development of teaching in which a blended learning methodology was applied was high in both groups (Group 1: $M = 4.90$ out of 5, $SD = 0.37$; Group 2: $M = 4.90$ out of 5, $SD = 0.34$). However, significant differences were found in student perceptions of the following items: item 1 (degree of prior knowledge) [$F_{(1,97)} = 3.89$, $p = 0.05$, $\eta^2 = 0.04$]; item 2 (degree of knowledge after completion of teaching) [$F_{(1,97)} = 4.38$, $p = 0.04$, $\eta^2 = 0.04$]; item 3 (clarity of the objectives of the course) [$F_{(1,97)} = 4.53$, $p = 0.04$, $\eta^2 = 0.50$], item 7 (facilitation of group work) [$F_{(1,97)} = 109.88$, $p = 0.00$, $\eta^2 = 0.54$], in this case with a high effect size. All of the results are in favor of the group in which the IPA had been applied. Although significant differences were also found in item 9 (possibilities that the development of the subject offers for future labor market insertion) [$F_{(1,97)} = 5.35$, $p = 0.02$, $\eta^2 = 0.05$], in this case in favor of the group in which no IPA had been used.

The open-ended responses on the scale were then analyzed. First, a categorization of the responses given by both groups to the open-ended questions was performed. Secondly, a frequency and percentage analysis by category was applied. Both procedures were performed with the program ATLAS.ti v.8 (see Table A4, from Appendix A). The results indicate that for *question 1* ("Do you think it is convenient to change anything in the subject? Why?"), the highest response percentage was found in Group 2 in the category "There is no need to change anything" (57.89%); in *question 2* ("In your opinion, which units of the current subject should be expanded? In theoretical content or in practical content? Why?"), the highest percentages were found in Group 1 in the category "Nothing" (37.50%) and in Group 2 in the category "Nothing" (54.17%). With respect to *question 3* ("In your opinion, which units of the current curriculum should be reduced? In theoretical content or in practical content? Why?"), the highest percentage was found in Group 2 in the "Nothing" category (70%). With regard to *question 4* ("Please give any indications you consider appropriate for the improvement of the development of the subject"), the highest percentage was found in Group 2 in the category "There is no need to change anything" (66.67%).

Regarding questions on teaching during the COVID-19 state of alert, it was found that in *question 1* ("How has work on the platform been in the weeks following the outbreak of the COVID-19 pandemic alert?"), Group 1 had the highest percentages, in the category "Difficult" (25%) and Group 2 in the category "Very good" (75%); in *question 2* ("After the COVID-19 pandemic alert, the resources of virtual meetings, email and platform support from the teacher have been."), Group 1 had the highest percentages, in the categories "Increasing the explanations by videoconference" (16.67%) and "Very good" (16.67%) and Group 2 "Very good" (66.67%). In *question 3* ("What would you have added as an aid to teaching during the state of alarm?"), Group 1 had the highest percentage in the categories "Nothing has been taught correctly" (33.3%) and "Nothing, everything has gone very well" (33.3%), and Group 2, in the category "Nothing, this type of methodology has facilitated the continuation of the course" (33.3%). In *question 4* ("Would you include any other resources than

those used by the teacher (virtual meetings, email and platform support, etc.) during the COVID-19 pandemic alert?"), Group 1 had the highest percentages in the "Nothing" category (33.33%) and, in Group 2, in the "Nothing" category (66.67%). Regarding *question 5* (What would you have eliminated as a teaching aid during the state of alarm?), Group 1 and Group 2 had the highest percentages, both in the "Nothing" category (50%).

3.5. Research Question 4

The responses of the students in Group 2 were analyzed, in order to study RQ4, for which the Scale for Evaluating the Functionality of the IPA "UBUVoiceAssistant" was applied. Questions 1 and 2 were respectively answered, on a Likert-type scale and with a yes/no question. The response rate was 87.75%. Regarding the first closed-ended question ("To consult the events of the subject (dates of delivery of practices, dates of tests type test, etc.), what resource do you use?"), 18.6% used the calendar offered by Moodle on the platform by default, 46.5% consulted the process calendar uploaded by the teacher on the UBUVirtual platform, 14% used the IPA, 11.6% consulted their colleagues and 9.3% had noted the information down since the beginning of the course.

Regarding the second closed-ended question ("Would you like to receive notifications through an IPA, either on your mobile phone or on another platform?"), 81.4% of students opted to continue receiving notifications on the subject and university activities through the IPA.

Answers were categorized for the study of the open-ended questions. Frequency and percentage analyses by category were then carried out on this categorization. All statistical analysis was processed with the ATLAS.ti v.8 tool. With respect to the first open-ended question ("What other information would you be interested in receiving from the UBUVoiceAssistant computer application?"), the answers showed that 10% of the users did not use the IPA, because of the need to open an Amazon account; 20% considered that the application was good, especially for people with special educational needs; 10% never used it; 10% indicated that they would like the application to include notifications when teachers upload resources on the platform; and 50% indicated that they would like the IPA to include information on all subjects during the academic year. Regarding the second open-ended question ("What information would you like the Moodle platform to give you?"), 60% indicated that they would like Moodle to give notices about activities, tests and exam dates. In addition, 40% indicated that they would like Moodle to give them information on resources or activities that the teacher would include in the platform. Regarding the third open-ended question ("If you are not using the UBUVoiceAssistant computer application, please tell us why and make suggestions for improvement"), 90% indicated that they used the IPA, although they would like information on all subjects to be included throughout the academic year. Meanwhile, 10% indicated that they used no IPA, as it is linked to an Amazon account, although they do find this type of application useful.

4. Discussion

The results indicate that the total accessing of the platform was lower in Group 1, where no IPA had been used, although the effect size was low. Likewise, more accessing of practical activities and teacher feedback was detected in Group 2, and more accessing of quiz-type activities in Group 1, with a high effect size in both cases (43% to 52%, respectively). With respect to learning outcomes, no better results were found in the group in which IPAs had been used. Likewise, student satisfaction with the development of the teaching was high in both groups, with no differences between either one. However, significant differences were detected for student perceptions of their knowledge, both before and after starting to teach. Differences were also found for student perceptions of the development of group work, which was higher in Group 2. Furthermore, in the qualitative study of the responses, greater satisfaction was found in the group in which IPAs had been applied. Along these lines, although both groups were satisfied with the development of the thematic units, the highest percentage was found in the group in which IPAs had been applied. In addition, the group in which no IPA had been implemented perceived the work during the state of alarm of the COVID-19 health crisis as more

difficult than the group in which IPA had been used, a group that perceived the work during this period as very satisfactory. Along these lines, the group that had not implemented IPA indicated that more videoconferencing would have been necessary, and only 16.6% perceived that teaching had been “very good”, compared to 66.67% of the group that had implemented IPAs. In addition, this group explained that the methodology in use had facilitated the smooth development of teaching during this period. Nevertheless, both groups perceived the teaching resources used during the health crisis as adequate, although the percentage satisfaction was always higher in the group in which IPAs were implemented. These results support those found in other research on: the use of advanced learning technologies in the LMS as a good resource for learning regulation [13]; the use of advanced technologies in LMS learning with personalized attention [2,12,14]; the use of PBL in LMS environments for increasing collaborative work [6,7]; and the use of LMS with additional technologies, which, together with a pedagogical model similar to the one applied in this study [15], increased the motivation and the effectiveness of learning among students [3]. In addition, specifically in the group with access to an IPA, greater satisfaction was found with the teaching–learning process [22], with teacher guidance in the teaching–learning process [23,24], and greater general satisfaction [44].

Regarding the assessment of students who had used IPA, it can be seen that the percentage of systematic use was around 14%, 66% of students opted for more visual resources within the Moodle platform (such as the default use of Moodle in the LMS and the calendar of processes and procedures that the teacher has included on the platform), and 20% of students used none at all. In addition, over 80% of students said they would like to receive information on assessment and test delivery processes and procedures through the Moodle platform with an IPA, as well as other information related to cultural events and events related to their area of knowledge at the university. In addition, some fears were expressed that these devices could invade privacy were linked to a reluctance to use IPAs. In summary, students appreciated the possibilities of using IPAs in university settings [45–47]; however, they understand that it is a new technology in this field and consider that there are aspects to be improved, both in terms of functionality and interface presentation [48–53].

5. Conclusions

The results of this study should be treated with caution, because we have worked with convenience sampling that assembled a group of students from the specific knowledge area of Health Sciences. In addition, the results point to the existence of strange variables that may influence the results, such as the learning history of the participants. Future studies will therefore be aimed at increasing both the size of the sample and the knowledge branch of each student, as well as evaluating the student records of collaborative learning. Nevertheless, despite the areas of research improvement, it should be noted that there is very little research that refers to the use of IPAs as a support for university teaching, since their preparation and use in LMS requires a complex technological and fieldwork framework.

The development of teaching in the university context is increasingly justified by the blended learning design and works towards the inclusion of different additional technologies and PBL resources. Within this framework, the pedagogical design of blended learning spaces in LMS is key to the consolidation of the teaching–learning process. Every day, technology offers new resources that can be incorporated into the LMS, including the use of an IPA. Its use is just beginning and requires important technical adjustments, although it is a very promising resource. University teaching has to implement further digitalization and move towards what has been called the smart university. This idea is gaining in strength, and situations such as the COVID-19 health crisis have only accentuated this trend. It is a present need as much a future one, that must be researched from both a technological and a pedagogical perspective, as well as from instructional standpoints. Moreover, both fields have to go hand in hand, since the functionality of technological resources has to be validated in both fields in an interactive manner, reiterating the need for further studies of blended learning. In addition, it is important to consider that the usage of a voice assistant could help students on their learning process, especially during the COVID-19 crisis, with the selected students specifically enrolled on the

Health Science degree at the university. We believe that it is important to research about the advanced technological tools available during the current pandemic situation and how those tools can help all Health Science degree students during their learning path, remembering that in our case, the students sample for this study was taken from students within the area of Health Science. As a potential path for future work, we could consider researching how technological aids influence the mood of students studying for degrees who will be directly confronted with situations such as COVID-19.

In summary, this study has contributed innovative results for university learning environments on the use of new technologies: particularly the LMS that incorporates an IPA. Nevertheless, this study has its limitations. As has been indicated, the study has worked with a specific sample size. Future studies will be directed towards expanding the sample, in terms of its size and the heterogeneity of the participating students. Likewise, some qualitative elements have been included in this investigation, although additional elements must be included in future studies, with which triangulation techniques may be applied, to expand the validity of the results. The inclusion of qualitative elements is a great challenge for the advancement of student assessment within virtual university environments. Nevertheless, advancement in this field can only happen with greater investment in both resources and investigation, to confront this challenge with greater assurance.

6. Patents

UBUVoiceAssistant Computer application is in the process of being registered [60].

Supplementary Materials: The following are available online at <http://www.mdpi.com/1660-4601/17/15/5618/s1>, Table S1: Course Development Rating Scale, Table S2: IPA Functionality Rating Scale “UBUVoiceAssistant”.

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Appendix A

Table A1. Two independent samples test in parametric test.

Scale of Metacognitive Strategies ACRAr [58]	<i>U</i> Mann-Whitney	<i>p</i>
1. I am aware of strategies (exploration, underlining, headings) that help me concentrate.	85.5	0.62
2. I am aware of learning strategies that help me to memorize (repetition and mnemonic rules, etc.).	61	0.10
3. I am aware of the strategies that help me to elaborate the information (drawings or graphs, mental images, etc.)	75.5	0.35
4. I am aware of the importance of organizing information by making outlines, sequences, diagrams, maps etc.	95.5	0.98
5. When I need to remember information for an exam, work, etc., I use mnemonic strategies, drawings, concept maps, etc.	92	0.85
6. I am aware that in order to remember information on an exam, it is useful for me to make mental connections with this information.	86	0.63
7. When I prepare an exam, I use strategies to order the information (scripts, diagrams...).	70	0.23
8. I plan the study by selecting the strategies that I think will be most effective.	84.5	0.59
9. Before I answer the questions on a test, I use strategies that help me remember the information.	77	0.36
10. Before I start studying, I distribute the time between all the subjects I have to learn.	92.5	0.87
11. I take note of the tasks I have to perform in each subject.	94	0.93
12. When the exams come up, I make a work plan establishing the time to be devoted to each topic.	87.5	0.70
13. I dedicate a time to each part of the material to study that is proportional to its importance or difficulty.	68	0.19
14. When I study, I check the strategies that work best for me.	93	0.89
15. At the end of an exam, I check the answers recalling the information studied.	87	0.68
16. If the strategies I use to “learn” are not effective, I look for others.	96	1.00
17. I keep the strategies working for me to remember information.	88	0.70

Table A2. Analysis of the asymmetry and kurtosis values of the distribution.

Scale of Metacognitive Strategies ACRAR [58]	Range	Min	Max	M	SD	Skewness		Kurtosis	
						S	N	S	N
1. I am aware of strategies (exploration. underlining. headings) that help me concentrate.	2.00	2.00	4.00	3.17	0.63	−0.17	0.41	−0.32	0.81
2. I am aware of learning strategies that help me to memorize (repetition and mnemonic rules, etc.).	2.00	2.00	4.00	3.30	0.63	−0.40	0.41	−0.44	0.81
3. I am aware of the strategies that help me to elaborate the information (drawings or graphs. mental images. etc.)	3.00	1.00	4.00	3.17	0.85	−0.70	0.41	−0.29	0.81
4. I am aware of the importance of organizing information by making outlines, sequences, diagrams, maps etc.	2.00	2.00	4.00	3.43	0.66	−0.83	0.41	−0.22	0.81
5. When I need to remember information for an exam. work. etc., I use mnemonic strategies. drawings. concept maps. etc.	3.00	1.00	4.00	3.30	0.77	−1.08	0.41	1.18	0.81
6. I am aware that in order to remember information on an exam, it is useful for me to make mental connections with this information.	3.00	1.00	4.00	3.40	0.65	−1.46	0.41	4.33	0.81
7. When I prepare an exam, I use strategies to order the information (scripts, diagrams...).	3.00	1.00	4.00	3.20	0.86	−1.09	0.41	0.91	0.81
8. I plan the study by selecting the strategies that I think will be most effective.	2.00	2.00	4.00	3.00	0.76	0.00	0.41	−1.22	0.81
9. Before I answer the questions on a test, I use strategies that help me remember the information.	3.00	1.00	4.00	3.13	0.71	−0.81	0.41	1.52	0.81
10. Before I start studying, I distribute the time between all the subjects I have to learn.	3.00	1.00	4.00	3.13	0.83	−0.64	0.41	−0.26	0.81
11. I take note of the tasks I have to perform in each subject.	2.00	2.00	4.00	3.10	0.73	−0.18	0.41	−1.05	0.81
12. When the exams come up, I make a work plan establishing the time to be devoted to each topic.	3.00	1.00	4.00	3.07	0.88	−0.75	0.41	0.08	0.81
13. I dedicate a time to each part of the material to study that is proportional to its importance or difficulty.	3.00	1.00	4.00	2.93	0.84	−0.89	0.41	0.86	0.81
14. When I study, I check the strategies that work best for me.	3.00	1.00	4.00	3.29	0.67	−1.22	0.41	3.29	0.81
15. At the end of an exam, I check the answers recalling the information studied.	3.00	1.00	4.00	3.21	0.89	−1.07	0.41	0.51	0.81
16. If the strategies I use to “learn” are not effective, I look for others.	3.00	1.00	4.00	3.37	0.73	−1.40	0.41	2.50	0.81
17. I keep the strategies working for me to remember information.	2.00	2.00	4.00	3.50	0.42	−1.38	0.41	3.99	0.81

Note. M = mean age; SD = standard deviation; A = asymmetry; K = kurtosis; ASE = asymmetry standard error; SEK = kurtosis standard error.

Table A3. Single factor fixed-effects ANOVA (use of IPAs vs. non-use)

	G1 N = 57	G2 N = 40	$F_{(1,97)}$	p	η^2
	$M (SD)$	$M (SD)$			
1. When you started the course your previous knowledge was at one level.	3.86(0.58)	4.05(0.22)	3.89	0.05 *	0.04
2. At the end of the course your knowledge is at one level.	4.00(0.50)	4.20(0.41)	4.38	0.04 *	0.04
3. In your opinion, the objectives of the course have been clear.	4.00(0.53)	4.23(0.48)	4.53	0.04 *	0.05
4. In your opinion, the concepts worked on in the course have been clear.	4.93(0.32)	4.85(0.48)	0.96	0.33	0.01
5. In your opinion, the practices have helped to understand the theoretical concepts.	4.79(0.73)	4.93(0.30)	1.27	0.26	0.01
6. Feedback from the teacher has been quick and accurate.	4.88(0.47)	4.93(0.30)	0.34	0.56	0.00
7. In your opinion, group work has been facilitated.	3.95(0.51)	4.90(0.40)	109.88	0.00 *	0.54
8. In your opinion, all the contents explained in the teaching guide have been addressed.	4.00(0.40)	4.15(0.50)	2.94	0.09	0.03
9. In your opinion, the skills you have developed in this subject can increase your chances of finding work.	4.89(0.40)	4.68(0.50)	5.35	0.02 *	0.05
10. The expectations you had when you enrolled in this course have been met.	4.88(0.50)	4.88(0.40)	0.00	0.98	0.00
11. In your opinion, the procedure and the evaluation criteria were clearly explained	4.88(0.43)	4.83(0.44)	0.34	0.56	0.00
12. In your opinion, the various assessment tests (practical, project-based learning) facilitated learning	4.89(0.45)	4.83(0.45)	0.57	0.45	0.01
13. In your opinion, the use of UBUVirtual as an online teaching platform has been	4.77(0.50)	4.87(0.45)	0.71	0.40	0.01
14. In your opinion, the use of questionnaires to evaluate the development of each unit has facilitated the understanding of it.	3.98(0.44)	3.80(0.61)	2.93	0.09	0.03
15. In your opinion, the difficulty of the subject is at one level.	4.79(0.60)	4.90(0.30)	1.18	0.28	0.01
16. Your level of satisfaction with the development of the practical activities has been	4.72(0.73)	4.88(0.40)	1.51	0.22	0.02
17. Your level of satisfaction with the development of the subject has been.	4.75(0.69)	4.78(0.53)	0.03	0.87	0.00
18. In your opinion, with respect to the rest of the subjects taken in the degree, you value this subject.	4.90(0.37)	4.90(0.34)	0.00	0.96	0.00

* $p < 0.05$.

Table A4. Categorization of the answers to the open questions of the scale. Analysis of percentages and frequencies found with ATLAS.ti v. 8

	Question 1 n = 19		Question 2 n = 24		Question 3 n = 9		Question 4 n = 6		Question 1. COVID-19 n = 8		Question 2 COVID-19 n = 6		Question 3 COVID-19 n = 3		Question 4 COVID-19 n = 2		Question 5 COVID-19 n = 2	
	F	%	F	%	F	%	F	%	F	%	F	%	F	%	F	%	F	%
Group 1: Development has been good	2	10.53	0	0.00	0	0.00	0	0.00	0	0.00	0	0.00	0	0.00	0	0.00	0	0.00
Group 1: Further explanations of the content of the practices	1	5.26	0	0.00	0	0.00	0	0.00	0	0.00	0	0.00	0	0.00	0	0.00	0	0.00
Group 1: Increase practices	1	5.26	0	0.00	0	0.00	0	0.00	0	0.00	0	0.00	0	0.00	0	0.00	0	0.00
Group 1: Many deliveries during state of alarm	1	5.26	0	0.00	0	0.00	0	0.00	0	0.00	0	0.00	0	0.00	0	0.00	0	0.00
Group 1: Not	1	5.26	0	0.00	0	0.00	0	0.00	0	0.00	0	0.00	0	0.00	0	0.00	0	0.00
Group 1: Suitable	1	5.26	0	0.00	0	0.00	0	0.00	0	0.00	0	0.00	0	0.00	0	0.00	0	0.00
Group 1: Difficult	0	0.00	0	0.00	0	0.00	0	0.00	2	25.00	0	0.00	0	0.00	0	0.00	0	0.00
Group 1: I don't think anything	0	0.00	0	0.00	1	10.00	0	0.00	0	0.00	0	0.00	0	0.00	0	0.00	0	0.00
Group 1: Increasing the explanations by videoconference	0	0.00	0	0.00	0	0.00	0	0.00	0	0.00	1	16.67	0	0.00	0	0.00	0	0.00
Group 1: Nothing	0	0.00	9	37.50	1	10.00	0	0.00	0	0.00	0	0.00	0	0.00	1	33.33	1	50.00
Group 1: Nothing has gone very well	0	0.00	0	0.00	1	10.00	0	0.00	0	0.00	0	0.00	0	0.00	0	0.00	0	0.00
Group 1: The development has been very good	0	0.00	0	0.00	0	0.00	1	16.67	0	0.00	0	0.00	0	0.00	0	0.00	0	0.00
Group 1: Very good	0	0.00	0	0.00	0	0.00	0	0.00	0	0.00	1	16.67	0	0.00	0	0.00	0	0.00
Group 1: Nothing has been taught correctly	0	0.00	0	0.00	0	0.00	0	0.00	0	0.00	0	0.00	1	33.33	0	0.00	0	0.00
Group 1: Nothing has gone very well	0	0.00	0	0.00	0	0.00	0	0.00	0	0.00	0	0.00	1	33.33	0	0.00	0	0.00
Group 2: Increasing practical classes	0	0.00	1	4.17	0	0.00	0	0.00	0	0.00	0	0.00	0	0.00	0	0.00	0	0.00
Group 2: Increasing the number of theoretical class	1	5.26	1	4.17	0	0.00	0	0.00	0	0.00	0	0.00	0	0.00	0	0.00	0	0.00
Group 2: Nothing	0	0.00	13	54.17	7	70.00	0	0.00	0	0.00	0	0.00	0	0.00	2	66.67	1	50.00
Group 2: There is no need to change anything	11	57.89	0	0.00	0	0.00	4	66.67	0	0.00	0	0.00	0	0.00	0	0.00	0	0.00
Group 2: To practice in real centres	0	0.00	0	0.00	0	0.00	1	16.67	0	0.00	0	0.00	0	0.00	0	0.00	0	0.00
Group 2: Very good	0	0.00	0	0.00	0	0.00	0	0.00	6	75.00	4	66.67	0	0.00	0	0.00	0	0.00
Group 2: Nothing this type of methodology has facilitated the continuation of the course	0	0.00	0	0.00	0	0.00	0	0.00	0	0.00	0	0.00	1	33.33	0	0.00	0	0.00
Totals	19	100	24	100	10	100	6	100	8	100	6	100	3	100	3	100	2	100

Note. F = frequency; % = percentage.

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4.2 Article 2: *Moodle LMS Integration with Amazon Alexa: A Practical Experience*

This article is available at *Applied Sciences* (ISSN 2076–3417), an international, peer-reviewed, open-access journal on all aspects of applied natural sciences, published semimonthly online by MDPI. It is an open-access journal, free for readers, with article processing charges (APC) paid by authors or their institutions, and it is indexed within Scopus, SCIE (Web of Science), Inspec, CAPlus/SciFinder, and many other databases, with a rapid publication process where manuscripts are peer-reviewed and a first decision is provided to authors approximately 13.8 days after submission, with acceptance to publication undertaken in 3.5 days.

Applied Sciences can be found on the Journal Citation Report database, within the category *ENGINEERING, MULTIDISCIPLINARY - SCIE*, listed in the second quartile, based on its Journal Impact Factor (JIF) (Q2 JIF = 58.33). At the time the paper was published, the journal ranked 38th out of 90 with a Journal Impact Factor (JIF) of 2.679 and a Journal Impact Factor Without Self Citations of 2.219 (See Figure 4.4).

Regarding the current status of the article, and based on metric data from *Web of Science*, the paper has 3 citations and 48 references (see Figure 4.5). As well, from the journal's metric data, it can be found that the article has had 1279 views of its abstract and 1965 views of the full document since the date of publication (See Figure 4.6).

Publishing Date: September 29th, 2020

Journal Name: Applied Sciences (ISSN 2076–3417)

Journal Rank: Q2

Impact Factor: 2.679 (2020); 5-Year Impact Factor: 2.736 (2020)

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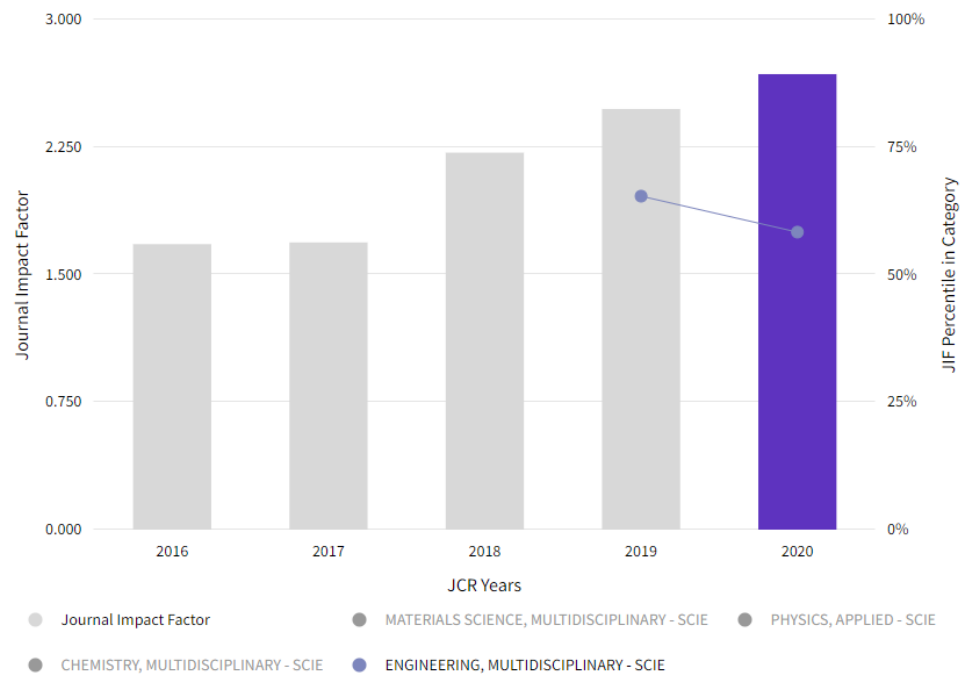


Figure 4.4: Article 2 - Journal Impact Factor 2020. (Source: [96])

Moodle LMS Integration with Amazon Alexa: A Practical Experience

By: Ochoa-Orihuel, J (Ochoa-Orihuel, Javier) ¹; Marticorena-Sanchez, R (Marticorena-Sanchez, Raul) ¹; Saiz-Manzanares, MC (Saiz-Manzanares, Maria Consuelo) ²
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Abstract

The frequency of interaction between teachers and students through Learning Management Systems (LMSs) is continuously rising. However, recent studies highlight the challenges presented in current LMSs to meet the specific needs of the student, regarding usability and learnability. With the motivation to support the research of effectiveness when using a Voice User Interface (VUI) for education, this paper presents the work done (RQ1) to build the basic architecture for an Alexa skill for educational purposes, including its integration with Moodle, and (RQ2) to establish whether Moodle currently provides the necessary tools for voice-content creation for develop voice-first applications, aiming to provide new scientific insight to help researchers on future works of similar characteristics. As a result of this work, we provide guidelines for the architecture of an Alexa skill application integrated with Moodle through safe protocols, such as Alexa's Account Linking Web Service, while our findings ratify the need for additional tooling within Moodle platform for voice-content creation in order to create an appealing voice experience, with the capabilities to process Moodle data structures and produce sensible sentences that can be understood by users when spoken by a voice device.

Keywords

Author Keywords: Moodle LMS; Amazon Alexa; education; e-learning; Intelligent Personal Assistant; voice-content; usability

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Figure 4.5: Article 2 - Record from the Web of Science. (Source: [97])

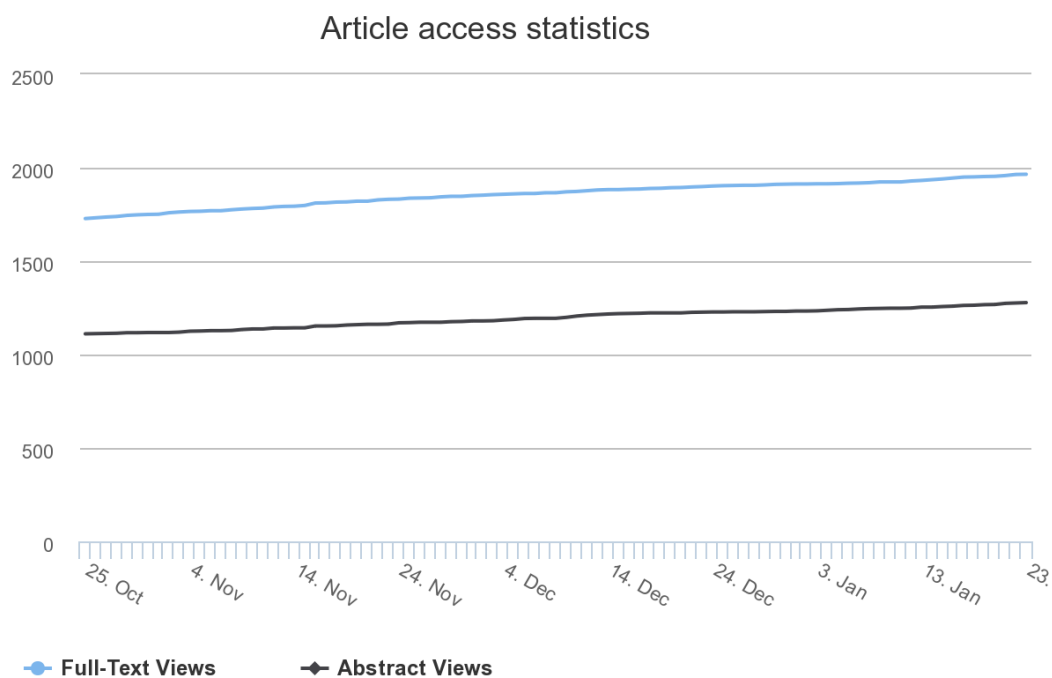


Figure 4.6: Article 2 - Access Statistics. (Source: [98])

Article

Moodle LMS Integration with Amazon Alexa: A Practical Experience

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Abstract: The frequency of interaction between teachers and students through Learning Management Systems (LMSs) is continuously rising. However, recent studies highlight the challenges presented in current LMSs to meet the specific needs of the student, regarding usability and learnability. With the motivation to support the research of effectiveness when using a Voice User Interface (VUI) for education, this paper presents the work done (RQ1) to build the basic architecture for an Alexa skill for educational purposes, including its integration with Moodle, and (RQ2) to establish whether Moodle currently provides the necessary tools for voice-content creation for develop voice-first applications, aiming to provide new scientific insight to help researchers on future works of similar characteristics. As a result of this work, we provide guidelines for the architecture of an Alexa skill application integrated with Moodle through safe protocols, such as Alexa's Account Linking Web Service, while our findings ratify the need for additional tooling within Moodle platform for voice-content creation in order to create an appealing voice experience, with the capabilities to process Moodle data structures and produce sensible sentences that can be understood by users when spoken by a voice device.

Keywords: Moodle LMS; Amazon Alexa; education; e-learning; Intelligent Personal Assistant; voice-content; usability

1. Introduction

Education is continuously challenged to achieve improvements on its learning processes and student performance [1]. The needs of learning have been changing over time, due to the rapid adoption of instant communication and the increase of information availability [2]. New teaching and learning methodologies have drastically altered education during the twenty-first century [3], with the integration of technological resources such as virtual platforms and hypermedia resources within the teaching-learning process, as well as other methodological techniques such as project-based or problem-based learning [4,5].

Pedagogy supporting deeper learning, which involves collaborative, informed, and personalized learning [6], has been determined to be more successful when helping students in achieving a more detailed understanding of modern skills [7]. The core will be a combination of personalization, collaboration, and informalization (informal learning), with traditional institutions finding the need to experiment with new formats and strategies for educating, providing them with the possibilities to offer relevant, effective and high-quality learning experiences [8]. However, while it has been identified improvement towards the student outcome brought by the use of collaborative learning [9,10],

additional factors have to be considered by teachers and instructors to achieve an effective and guaranteed learning [11,12].

Learning Management Systems (LMS) are considered a critical and decisive key of modern e-learning [13–15], and while sometimes they are regarded as just a tool to deliver content, LMSs provide the means to create engagement between the students, the instructors, and the content [16]. There is a continuous increase on the frequency that teachers and students interact through LMSs [17], and even though institutions have customized their own LMS instances to meet the instructors' needs [18], recent studies highlight the challenges presented in current LMSs to meet the specific needs of the student, regarding usability and learnability [19,20], which can cause a decline on their engagement with the platform and impact their learning outcomes [21,22].

The need to innovate and experiment with cutting-edge technology provided the opportunity and motivation to develop an Alexa skill to support the research effectiveness of utilizing a VUI for education, delivering notifications and upcoming events related to student's courses, and study if, and how, VUIs could be used as an educational tool to enhance the student's experience [23]. To such end, the Alexa skill would need the capability to integrate with Moodle. Furthermore, the Alexa skill would be developed to a production-ready level, to be released as soon as it is ready, and become publicly available to any user of Amazon Alexa. Finally, as the relevance of a robust architecture for IPAs is trending with several IPA architectures proposals in recent years [24], this project would aim as well to validate the existing knowledge available from scientific studies of similar nature, testing that such knowledge helps in our development to overcome issues we might encounter, and provides us with guidelines to implement a solid foundation for our application. Our work and findings would then be presented to provide new scientific insight for helping and guiding researchers on future works of similar characteristics, disclosing the successful and failed decisions and technical implementations taken along the way, along with the analysis and results of the usability of the skill itself.

Based on the research and motivation noted above, the research questions in this study are as follows. (RQ1) To build the basic architecture for an Alexa skill for educational purposes, including its integration with Moodle; (RQ2) to establish whether Moodle currently provides the necessary tools for voice-content creation for developing voice-first applications.

The remainder of this work is structured as follows. First, Section 2 presents a brief review of related work, followed by Section 3 which contains the methodology for our research and the implementation and development of the Alexa skill. Next, Section 4 describes the usability evaluation done after releasing the Alexa skill publicly, and Section 5 contains the analysis and results of our work. Finally, Section 6 discusses the main conclusions and limitations derived from our research.

2. Related Work

After an extensive search within multiple scientific databases (Scopus, Web of Science, ScienceDirect, Springer, Wiley, and Taylor & Francis), selected articles were reviewed in order to assess the state-of-art in research on the use of Voice User Interfaces for education. We divided the review of the found literature by first looking at the studies where there was no use of a smart speaker, followed by a review of those studies which did have some use of smart speakers. For this division, the concept of smart speaker was defined as a device which provides a way for people to interact with them by the use of their voice, without the needs to touch the actual device [25]. As well we created a comparison table to help us find commonalities between the studies, identifying the technical components, platforms, frameworks, tools, and libraries used on each of them (see Table 1).

Table 1. Comparison of studies.

Article	Voice Platform	LMS	Development Tools
Grujic et al. [26]	Interactive Voice Response (IVR)	Moodle	-
Pereira et al. [27]	Telegram app	open-MOOC	PHP, MYSQL
Todorov et al. [28]	Android app	DeLC 2.0	Java, CMUSphinx [29]
Kita et al. [30]	Google Simulator	Moodle	PHP, DialogFlow [31]
Kita et al. [32]	Google Home / Amazon Alexa	Moodle	PHP, DialogFlow, Alexa Cloud service
Laeq and Memon [33]	-	Moodle	Java, JADE (Java Agent Development Framework) [34]
Melton [35]	Amazon Alexa	Moodle	LAMP framework, Let's Encrypt

2.1. Studies with no Smart Speakers Use

In his work, Grujic et al. [26] propose a solution which links an E-education system, such as Moodle, via Interactive Voice Response (IVR), a technology that enables a computer to interact with humans through the use of voice and tones input produced by a keypad. The use of IVR applications could prove to be very beneficial, allowing the extension of operational business hours, reducing the waiting time for callers, and providing service to multiple users simultaneously, which would enhance service quality and the overall student's satisfaction. This study is a straightforward specification on how the prototype was implemented, and so there are no conclusions or outcomes we could use on our work regarding the impacts that such a prototype has on the users.

A solution for peer-to-peer (P2P) assessment using voice recordings is researched by Pereira et al. [27]. The authors implemented a chatbot using an existing Instant Messaging (IM) platform (Telegram), which integrated with a massive open online course (MOOC). Using the API provided by Telegram, the chatbot was developed to interact in a conversation with the student. There could be two possible conversation paths. On a normal interaction, the chatbot would ask a question to the user via text message. The user would then answer using the microphone capabilities of Telegram app, and the audio would be sent back to the chatbot for further processing and assessment. The second conversation path would be triggered if the user would send the custom-made evaluation command. The chatbot would present the original text question and the given audio answer so that the user could listen to it and provide a grade (on a scale from 1 to 10).

A prototype implementation of a VUI is discussed in the work by Todorov et al. [28]. The Learning Intelligent System for Student Assistance or LISSA, a name given to the prototype, is a personal assistant whose goal is to monitor the performance of tasks related to students' curriculum, to assist them along the learning process. LISSA's prototype takes the form of an Android app, implemented using Java programming language, and interacts with the DeLC 2.0 educational portal, which is a software project for developing an environment to support virtual education [36]. For our work, we found it highly beneficial to learn that several problems were found during the implementation of the LISSA's prototype and gather knowledge on how those issues were overcome. During the development process, it was found that the process for voice recognition was highly complex, categorized by the authors as an "entire scientific area". Todorov et al. [28], noted as well that recognizing voice commands does require a large amount of resources from the device, which impacted the drain of the device battery, considered by the authors as a valuable resource.

Kita et al. [30] argue that VUIs are quickly becoming suitable for various practical purposes in daily life, in addition to a VUI being an effective and intuitive interface to be used by many people, and so they describe the development process of a prototype VUI aiming for Moodle Quizzes used for educational purposes. Before learners decide to enroll into a course, a Moodle Quiz could be used as a tool that allows learners to quickly get an understanding of what can be learnt from the course and an appreciation of the educational gain the learners will achieve after its completion. The prototype developed by the author was made available to a limited number of users through Google Home smart devices. The conclusions of the study suggest that VUIs should aim to speak using short phrases, and that if there is need for long ones, then the VUI should inform users of the total time first, to avoid users to wonder when might it end. For this reason, the study concludes that content from an LMS must not be used without previous editing, to keep the learning experience through the VUI at its best. Furthermore, the study notes that the use of VUI for educational purposes is expected to have a positive effect on the learners' motivation due to the notion that learners "feel heard".

2.2. Studies Using Smart Speakers

In a more recent study, Kita et al. [32] continue their work related to the use of VUIs for educational purposes. In their latest work, the authors develop a voice app which allows searching for documentation regarding Moodle functions, with the use of voice commands, and has availability for both Google Home and Amazon Alexa devices (see Figure 1). The authors argue that such app would be helpful due to the rather common need to browse for documentation about operations methods and functions from Moodle when creating teaching material. The conclusions of the study denote as highly valuable the exploration of using VUIs as a channel to consolidate the interactions between LMSs and users. Moreover, the study emphasizes the need for the consideration of the advantages of choosing and implementing VUIs as user interfaces, while being aware of the existing limitations and drawbacks. Furthermore, the conclusions tease the future plan to extend the voice app with the capability to notify users about important activities, such as overdue assignments or short-coming events.

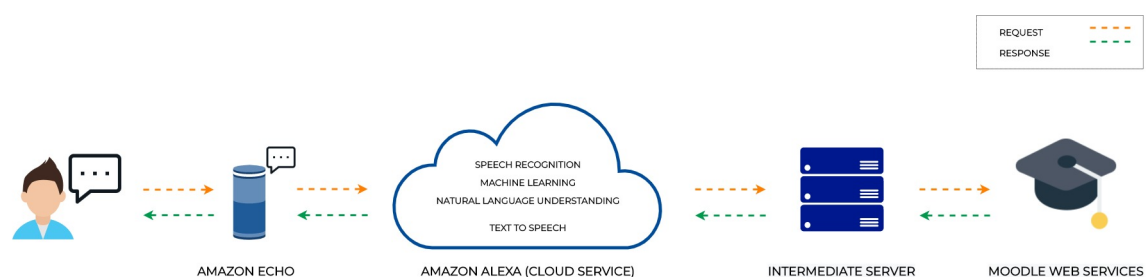


Figure 1. Graphical representation of Kita et al. [32] prototype architecture (Source: own authors' elaboration).

In their study, Laeeq and Memon [33] define the usability of LMS systems as one of the key features that determine the success or failure of those systems, and relates to previous studies concluding that e-learning environments are not evolving according to the needs of learners, with poor usability as the core difficulty, produced by multiple design, navigation, and user interface issues found in existing LMS systems. Laeeq and Memon [33] reasons that navigations and search are two key modules of any LMS which impact system usability directly, and so a user-friendly navigational system within an LMS system can aid users to accomplish their goals, keeping them engaged until they have achieved their purpose. The conclusions from the works of Laeeq and Memon [33] indicate that the students who did interact with Moodle using the prototype built for the study show "greater motivation and a high rate of task completion in a shorter time period", which presumes that integrating a voice-activated virtual assistant with an existing LMS has a distinguished and notable impact on students' performance.

The authors' suggestion is to generalize the system in order to gather further data, as the usability of the prototype was tested within just a pre-selected group of students.

The work by Melton [35] describes the development of an Alexa skill that aims to enhance the speed and convenience of accessing information in Moodle. The author proposes the idea that an Alexa Skill would allow users to access information from LMS systems more quickly and conveniently, with immediate benefits for the users through site announcements to all users, course announcements to students and teachers, and overall course grades and upcoming due dates to students (see Figure 2). Besides improvements on the capabilities and features of the prototype itself, the conclusions of this work reveal areas for improvement regarding VUI design of the skill, mentioning that usability tests show a possible improvement in user experience by reducing responses to only provide information about the most recent events, shorting out the spoken response from Alexa, as opposed to provide with all available event information at once. Moreover, the interest of adding visual content to support spoken responses on newer Alexa devices which might incorporate graphic displays is noted, besides the already existing voice interface.

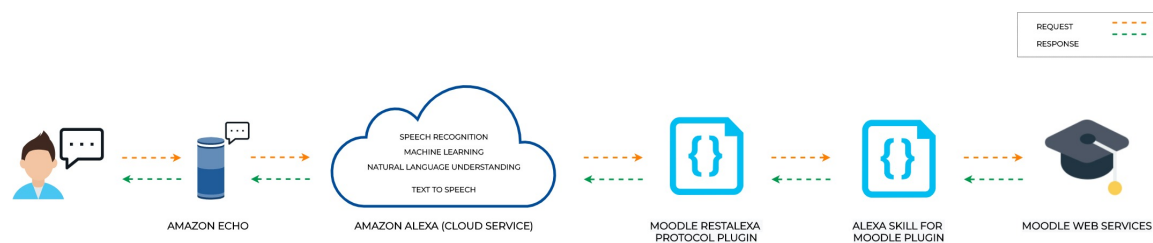


Figure 2. Graphical representation of Melton [35] prototype architecture (Source: own authors' elaboration).

3. Method

When a user speaks to a device with Alexa, the speech is streamed to the Alexa service in the cloud, which handles all speech recognition and conversion. Alexa service in the cloud processes the speech, determines what the user wants, recognizes if any of the available skills can fulfill the user's request and then sends a structured request to the particular skill [37]. A custom skill requires a cloud-based service to process the user's request and provide the proper response. As recommended by Amazon, the easiest way to build the cloud-based service for a custom Alexa skill is to use AWS Lambda. AWS Lambda is an Amazon Web Services (AWS) service that runs code only when it is needed and scales automatically, removing the need for provision or continuously running servers. The custom code for the Alexa skill is uploaded to AWS Lambda and the service does the rest, executing it in response to Alexa voice interactions and automatically managing the compute resources [37]. Additionally, due to the nature of the skill we implemented, our custom code required to be connected to a Moodle instance, as we had to take in use some of the functionalities provided by the Moodle Web Services.

The following sections explain more in detail the various modules that composed the final architecture of the custom Alexa skill we implemented for our research (see Figure 3).

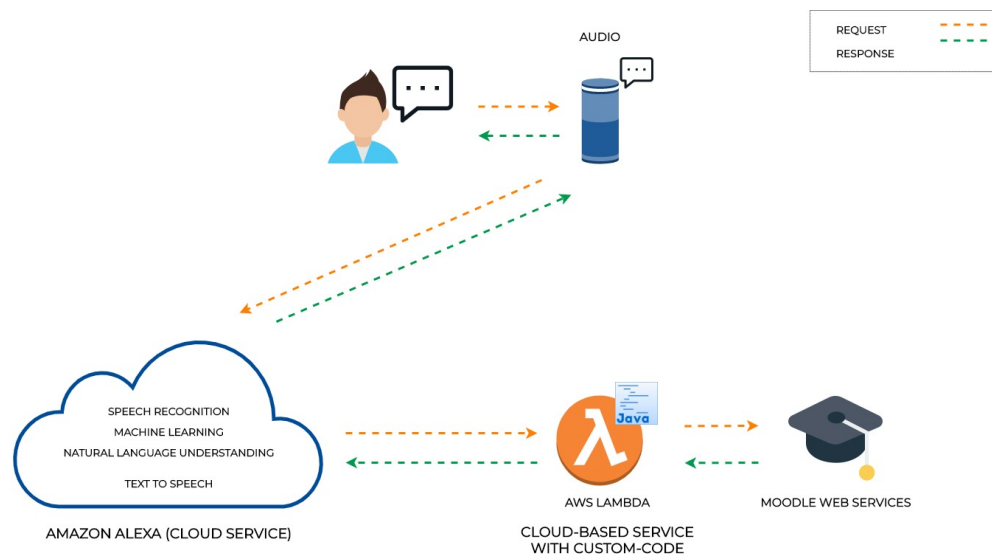


Figure 3. Diagram for processing a request by our custom Alexa skill (Source: own authors' elaboration).

3.1. Moodle Web Services

For the implementation of our prototype we are required to connect programmatically to Moodle. To be more precise, our prototype took in use the REST protocol, which becomes available automatically when enabling the Mobile Web Services. Mobile Web Services is a built-in web service designed to enable the interaction between mobile applications and Moodle [38]. This web service is required for running the official Moodle Mobile app, or if a third-party app explicitly requires it. By utilizing the Mobile Web Services, we are capable of exploiting the same information as the official Moodle app uses to provide features such as browse the content of courses, track personal progress, or view course grades [38]. It is important to notice that the Moodle release used for our test case was "3.7.4+ (Build: 20200117)".

For our prototype, we initially took in use three core API functions:

- "core_webservice_get_site_info", which returns site info, user info, and list web service functions.
- core_enrol_get_users_courses, which gets a list of course ids that a given user is enrolled in.
- core_calendar_get_calendar_events, which gets calendar events for a given user.

We aimed to combine the use of the above-mentioned Moodle functions in order to retrieve enough information to present to a user with the specific events related to courses and other user-related matters. Later in this chapter, there is a more detailed explanation of how these functions were used and integrated into our Alexa skill.

3.2. Alexa Skill Implementation

First, we had to decide what type of Alexa skill we needed to build. Alexa provides a set of built-in capabilities, referred to as skills. Users can access these new abilities by asking Alexa questions or making requests. However, the functionality to be implemented determines how the skill integrates with the Alexa service and so it dictates what kind of skill needs to be built [37]. At the time we began building the Alexa skill there were existing pre-built skill models from where to choose (See Figure 4), but none of them provided us with the kind of interaction that we would need the skill to perform, and so we decided to develop a custom interaction model skill or "Custom Skill", which can handle just about any type of request [37].

Within the Alexa service, an interaction model is similar to what a graphical user interface is for a traditional app. Instead of clicking buttons and selecting options from dialog boxes and graphical elements, users make their requests and respond to questions by voice. When users speak questions and make requests, Alexa uses the interaction model to interpret and translate the words into a specific request that can be handled by a particular skill [37]. An extract of the Alexa skill's intent schema can be seen on Listing 1. Additionally, to build a custom skill we need an internet-accessible endpoint where our cloud-based service would be hosted. Alexa service is already integrated with AWS Lambda (an Amazon Web Service offering), so it makes it simple to host and run the service with our custom logic. Due to the already existing knowledge from the researchers, we decided to use this service and develop the cloud service for our skill using Java technology, specifically Java SE 8, which is supported by AWS Lambda [37].

Listing 1: Intent Schema used for our custom skill.

```
{
  "interactionModel": {
    "languageModel": {
      "invocationName": "calendario de la ubu",
      "intents": [
        {
          "name": "AMAZON.CancelIntent",
          "samples": []
        },
        {
          "name": "AMAZON.HelpIntent",
          "samples": []
        },
        {
          "name": "AMAZON.StopIntent",
          "samples": []
        },
        {
          "name": "AMAZON.NavigateHomeIntent",
          "samples": []
        },
        {
          "name": "AMAZON.FallbackIntent",
          "samples": []
        },
        {
          "name": "CalendarIntent",
          "slots": [],
          "samples": [
            "Calendario"
          ]
        }
      ],
      "types": []
    }
  }
}
```

alexa developer console

Create a new skill

Cancel Create skill

Model: Custom Host: Provision your own

Skill name

Enter skill name

Skill name must have at least 2 characters. 50/50 characters

Default language

English (US)

More languages can be added to your skill after creation

1. Choose a model to add to your skill

There are many ways to start building a skill. You can design your own custom model or start with a pre-built model. Pre-built models are interaction models that contain a package of intents and utterances that you can add to your skill.

Custom Design a unique experience for your users. A custom model enables you to create all of your skill's interactions.	Flash Briefing Give users control of their news feed. This pre-built model lets users control what updates they listen to. "Alexa, what's in the news?"	Smart Home Give users control of their smart home devices. This pre-built model lets users turn off the lights and other devices without getting up. "Alexa, turn on the kitchen lights"	Music Give users complete control of their music. This pre-built model lets users search, pause, skip, or shuffle in your skill. "Alexa, play music by Lady Gaga"	Video Let users find and consume video content. This pre-built model supports content searches and content suggestions. "Alexa, play Interstellar"	Meetings This pre-built model leverages Alexa for Business APIs to allow users to search for and book available meeting rooms in their office. "Alexa, book a room"
--	--	---	--	---	--

2. Choose a method to host your skill's backend resources

You can provision your own backend resources or you can have Alexa host them for you. If you decide to have Alexa host your skill, you'll get access to our code editor, which will allow you to deploy code directly to AWS Lambda from the developer console.

Provision your own Provision your own endpoint and backend resources for your skill. This is recommended for skills that have significant data transfer requirements. You will not gain access to the console's code editor.	Alexa-Hosted (Node.js) Alexa will host skills in your account up to the AWS Free Tier limits and get you started with a Node.js template. You will gain access to an AWS Lambda endpoint, 5 GB of media storage with 15 GB of monthly data transfer, and a table for session persistence. Learn more	Alexa-Hosted (Python) Alexa will host skills in your account up to the AWS Free Tier limits and get you started with a Python template. You will gain access to an AWS Lambda endpoint, 5 GB of media storage with 15 GB of monthly data transfer, and a table for session persistence. Learn more
--	--	--

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Figure 4. Alexa Developer Console: View for creating a new skill.

3.2.1. Account Linking Web Service

We required an additional web service that would handle the Account Linking process with Alexa service when users enable the skill for the first time. In a nutshell, Account Linking is an Alexa service's feature that enables authentication with a third-party service, and it is based on the OAuth2 authentication protocol (see Perez [39] for more details on OAuth2 protocol). The process for linking an account is initiated from the Alexa mobile app, which redirects the user to an authorization url, previously configured on the Alexa Developer Console (see Figure 5). Users would have to sign in to the form presented on that url to authenticate themselves against the third party service. In case the authentication is successful, a call to the access token url is triggered to fetch an access token to accompany any further Alexa request, and the Account Linking process is concluded. Similar to the authorization url, the access token url must be previously configured [40]. Account Linking is not mandatory for an Alexa skill to function properly, but in our case we perceived it would be best to add the extra step of linking the Moodle account of the user before any interaction with the skill happened, and so we implemented this service using Java SE 8 and AWS Lambda as we did previously.

Our skill aimed to retrieve information from Moodle LMS, which made it mandatory for the skill to communicate with Moodle Web Services. The Alexa requests would have to carry the account token to successfully interact with the Moodle Web Services. To reach the token, our approach was to develop a traditional login web form (see Figure 6) where the user could input the username and password of their Moodle account and exchange those credentials for the token. To keep the highest security when handling the user's password for Moodle, we decided not to store the password at all. The user would input the username and password from the Moodle account on the login form and those credentials would be sent directly to Moodle via HTTPS request to the script located at `/login/token.php`, which will then exchange those credentials for the account token, to be used in the following requests to Moodle Web Services.

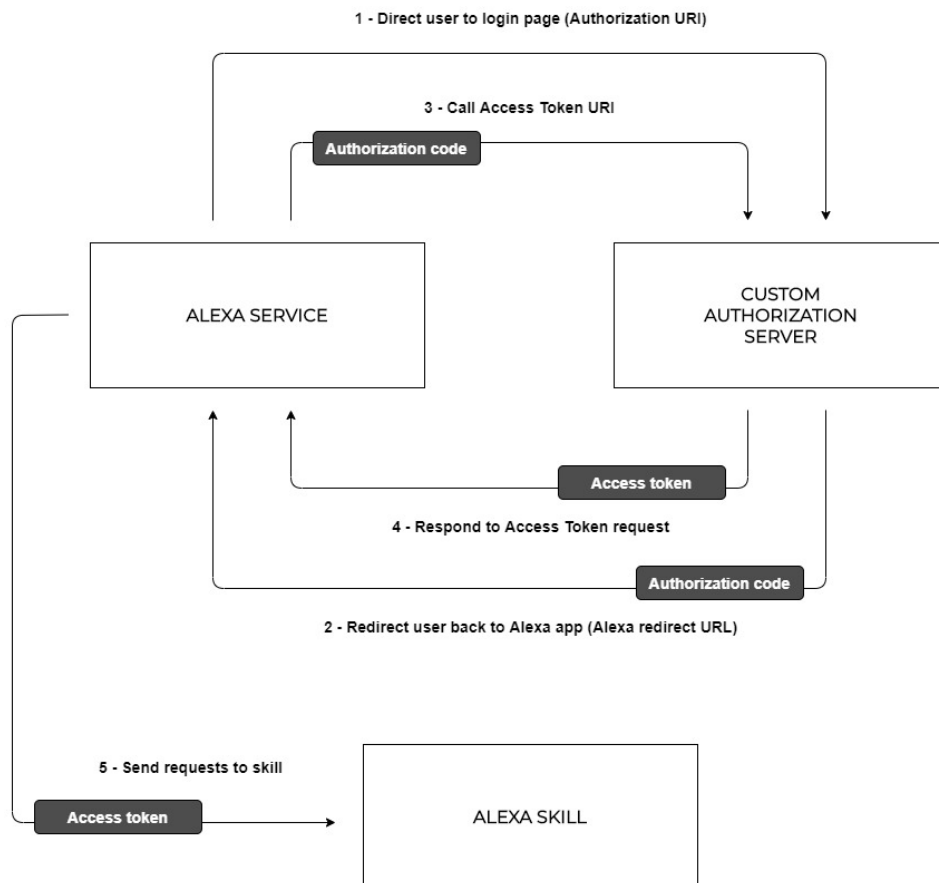


Figure 5. Account Linking flow for authorization code grant type (Source: own authors' elaboration).

Bienvenido

Por favor, introduce tus credenciales como miembro de la UBU.

Acceder

[Política de Privacidad](#)

Figure 6. Login web form screenshot (Source: own authors' elaboration).

All communication was achieved using HTTPS to ensure the protection of the privacy and integrity of the exchanged data while in transit. As happened with the passwords, we decided not to store the Moodle token anywhere either. However, we would require the token when requesting information to Moodle Web Services. To be able to keep the token without storing it ourselves, we decided to use the Alexa access token for this task (see Figure 7).

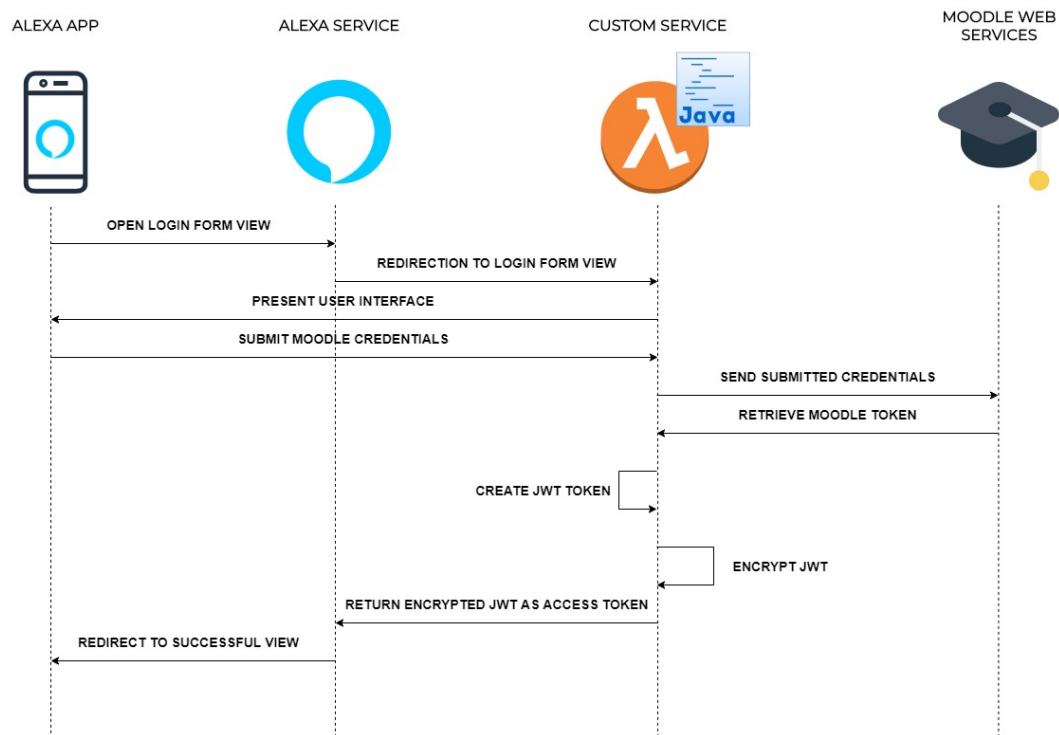


Figure 7. Flow diagram for Alexa access token exchange (Source: own authors' elaboration).

The Alexa access token is delivered on every Alexa request sent by the Alexa service, and allows for identifying the user which triggered the request. We took advantage of this feature and used the Alexa access token to store a JSON Web Token (JWT) created by us. The JWT would contain information that would allow us to identify the user (see Listing 2), including the Moodle account token previously exchanged through the login form. JWTs are an open industry standard RFC 7519 method for representing claims securely between two parties. As explained on the RFC formal document by Jones et al. [41], “the claims in a JWT are encoded as a JSON object that is used as the payload of a JSON Web Signature (JWS) structure or as the plaintext of a JSON Web Encryption (JWE) structure, enabling the claims to be digitally signed or integrity protected with a Message Authentication Code (MAC) and/or encrypted”.

Our JWT token would include three claims for us to use later on:

- **userId**, our own unique identifier for the user, not related to any identifier from Alexa service or Moodle.
- **username**, user's Moodle username.
- **moodleToken**, the token retrieved from Moodle after user's authentication through the login form.

With the implementation of the JWT token we were able to identify the user when needed, as well as being capable to interact with Moodle Web Services on user's behalf. However, we felt that passing the JWT token as plain text might be insecure due to the fact that the Moodle token of the user would be readable to any third party that might gain access to the JWT token. For this reason, we decided to encrypt the JWT token before passing it through to Alexa service. The main objective of cryptography is to keep data safe from unauthorized access.

Listing 2: JWT structure example.

```

Header: Algorithms and Token Types
{
  "alg": "HS256",
  "typ": "JWT"
}

Payload: Data
{
  "iss": "XXX",           // Public Claim
  "iat": XXX,             // Public Claim
  "userId": "XXX",        // Private Claim
  "username": "XXX",       // Private Claim
  "moodleToken": "XXX",    // Private Claim
}

Signature: results from Hash
{
  HMACSHA256(
    base64UrlEncode(header) + "." +
    base64UrlEncode(payload),
    secret)
}

```

Through cryptography we can achieve security by encoding messages in unreadable format so that the original message would only be read by the intended user [42]. While there are many encryption mechanisms currently available, we decided to use “Threefish” to securely encrypt the JWT token. “Threefish” is a large, tweakable block cipher, developed by Bruce Schneier, Niels Ferguson, Stefan Lucks, Doug Whiting, Mihir Bellare, Tadayoshi Kohno, Jon Callas, and Jesse Walker in 2008 [43]. It is defined for three different block sizes: 256 bits, 512 bits, and 1024 bits. We used 512 bits as the block size to encrypt the JWT token. The key is the same size as the block, and the tweak value is 128 bits for all block sizes [44].

Finally, we encoded the encrypted token using Base64 algorithm. The Base64 algorithm allows for encoding and decoding an object into ASCII format, and it is used in multiple cases, including URL encoding purposes [45]. By encoding the encrypted token we made sure the data integrity would remain during the sending and receiving of the token. The final encoded token is then ready to be sent back to Alexa service and complete the Account Linking process successfully. The encoded token would be then sent as part of any future Alexa request. Receiving the encoded token within the requests would allow us to identify the user who sent the request, and successfully communicate with Moodle Web Services on user’s behalf, as the Moodle account token would be contained within the JWT as claim, once it is decoded and decrypted.

3.2.2. Implementation Problems and Workarounds

Over the course of the development of the skill we confronted unexpected issues regarding the user experience when creating voice dialog from the information we got from Moodle Web Services. As mentioned in Section 3.1, we combine several Moodle functions to create the logic that would reach the calendar event data for the user. We utilize the function `core_enrol_get_users_courses` to retrieve the information regarding the course, such as the name of the course, and the function `core_calendar_get_calendar_events` to retrieve the actual information related to the events, such as name of the event, date of the event, etc.

We encountered the problem that certain properties of the elements of Moodle, such as the name of a course or the name of an event, might be specified by the administrator of such element in such manner that would not be directly compatible with audio streaming. For example, some event titles might contain special characters to help understand that the event is aimed for a specific group

of people (e.g., Project Presentation (Group 1) or Basics of Programming (Online)). Furthermore, course titles might be too long for an audio experience, where the user must listen to the full course name if events related are presented, which might exhaust the time and willingness of the user to listen to the full response for a long period of time. This problem with the user experience brought up a new issue, this time regarding the administration of the Alexa skill itself. How could an administrator of an element in Moodle, such as a calendar event, for example, be able to hear what the final user might experience through the Alexa devices, before making it publicly accessible? As an example, if a teacher could listen to what the students might hear regarding an event that is being newly added, the teacher is still able to edit the outcome until the audio experience achieves the expected level of quality and comprehension. However, in its current form, the only way for any person to hear what an event might sound like through our Alexa skill was to actually make the event public, without even knowing how it will really be spoken out by the Alexa device.

These problems were a direct risk for the purposes of our work. If we were to test the likelihood of users enjoying the use of our Alexa skill, we had to aim for the best user experience we could offer to begin with. As our work was not a technical research on Moodle integration with Amazon Alexa, we made the conscious decision to edit the interaction flow with Moodle. Instead using the Moodle function `core_calendar_get_calendar_events` to fetch the user events, we decided to create a file within our application which would contain the events information hard-coded within, and replace the use of the Moodle function by reading and processing that file when needed. By hard-coding the information on a file, we removed the flexibility of updating event data through Moodle, or any external service for that matter. The only way to update any event data, meaning adding new events, deleting unnecessary ones, or modifying any of the existing ones, could only be achieved by editing the file manually and deploying the application again on our cloud hosting service (in our case AWS Lambda service). On the other hand, this file contained all the necessary information we required for our skill to perform optimally. The file would contain event data in JavaScript Object Notation (JSON) format, which will allow us to have custom values such as the course name, as we wanted to be said by Alexa, the date of the event, on a standard ISO-8601, and other values what allowed us to build the audio output of the Alexa skill on a more user-friendly fashion, which would help to our research for understanding user's experience with Alexa (see example of event JSON on Listing 3).

Listing 3: Calendar event JSON example.

```
[
  {
    ...
  },
  {
    "eventId": "002",
    "eventTitle": "Final day for Early Stimulation course",
    "eventDate": "2020-06-26",
    "eventCourseId": "1685"
  },
  {
    ...
  }
]
```

4. Usability Evaluation

We confronted several issues while developing our Alexa skill. One of the conscious decisions we made was to hard-code part of the events' information on a file, as opposed to get the information programmatically from Moodle instance directly. This decision meant that, while any user with an account in Moodle would be able to access and interact with the Alexa skill, only those who were participants on the particular courses we had chosen and which events' information was included in

the file. However, as mentioned, any user with an account on Moodle would be able to access and interact with the Alexa skill, and that would include the introduction to the use of the skill, as well as the account linking process and other available paths of interactions.

Once our skill was fully developed, deployed, and publicly available, we began a usability evaluation to understand the performance and impact that the skill could have on the students. It is of importance to note that we did not recruit any student to participate in the evaluation of the skill. The students were told about the Alexa skill on the course presentation day and the goals of the project were explained to them. As part of the evaluation we aim to measure what would be the acceptance level of the Alexa skill and how students would adopt such innovation, understanding if students would interact with the skill willingly on their own. To increase the amounts of data measured over the evaluation period, we decided to boost the interest of students for using the skill on their own by offering an Alexa Echo Flex device as reward from a drawing between those students who would interact with the skill.

Totally, there were 61 students accounted to be part of the course to be used for the usability evaluation. Prior the beginning of this study, both the authorization of the Bioethics Committee of the University of Burgos and the informed consent of all participants were obtained in writing (see the Ethics Statement section at the end of this article). The student group was composed by 56 female and 5 male students, with further statistical data to be seen on Table 2.

Table 2. Description of the evaluation sample.

Participant Gender	Count	Mean Age	Standard Deviation Age
Male	5	22.00	2.24
Female	56	23.54	6.30
Total	61	23.36	6.01

The evaluation was conducted over the period of two months, from 1 February 2020 until 31 March 2020. Information regarding the usage of the skill was taken from the Analytics section found on the Alexa Developer Console (See Figure 8). This tool makes it possible to monitor many aspects on how the skill is being utilized by the users and how it is performing. These measurements will allow us to study if, and how, the technical performance of the skill might have a positive or negative impact on its usability, and detect those areas where problems might arise during the interaction of the users with the skill.

A short non-mandatory survey was given to students at the beginning of the course to better understand their familiarity with Amazon Alexa technology. This survey was composed of one question with dichotomous reply options (yes/no) and a second one with multi-choice question (see Table 3). The answers from this survey offered us information to create participant profiles, which could later on help us understand better the results obtained by the usage of the skill and the usability evaluation (see Figure 9). From the 26 students who participated in the survey, 12 of them (46.2%) answered that they had used a voice-activated device before this evaluation. Only one of the participants answered to use the device on a weekly basis, and ten of them answered to use it seldom.

Table 3. Initial survey to students (Extract taken from Saiz-Manzanares et al. [23]).

Survey Question	Possible Answers
Have you ever used a voice-activated device, similar to Alexa Echo devices?	Yes No Never Seldom
If so, how often do you use those devices?	Weekly Several times per week Daily

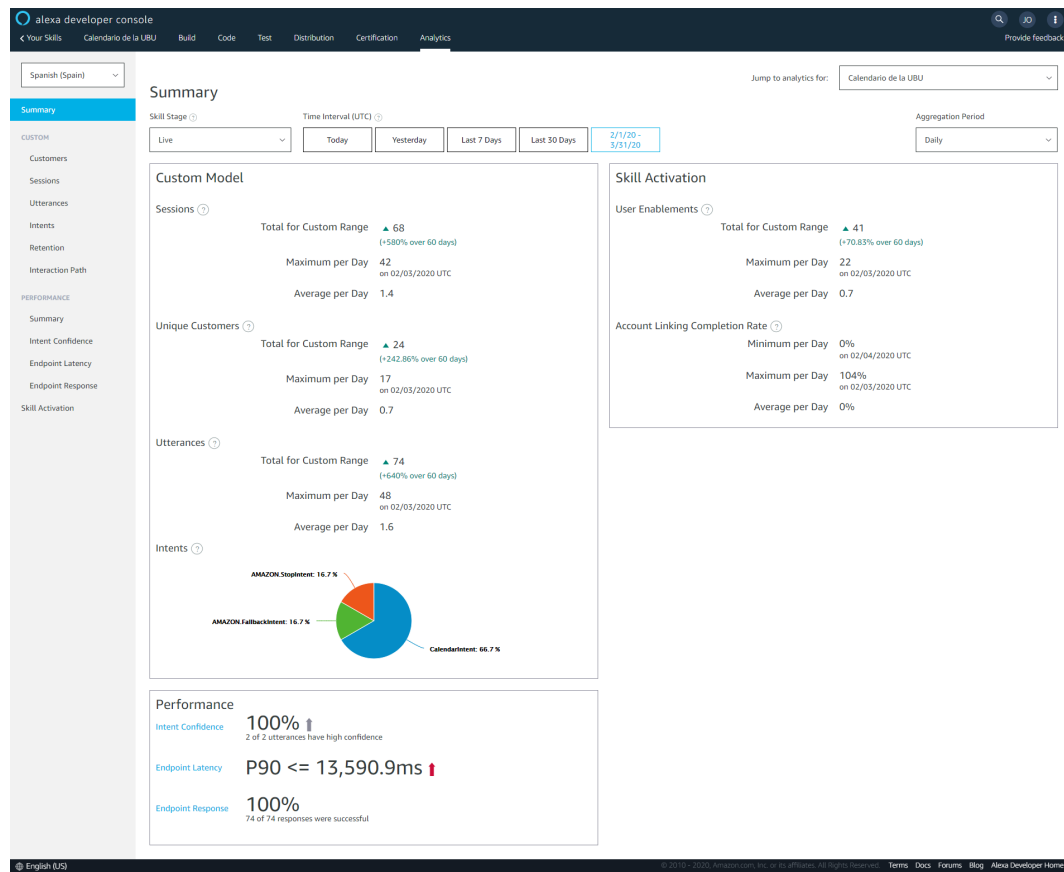


Figure 8. Screenshot of the Analytics section within the Alexa Developer Console.

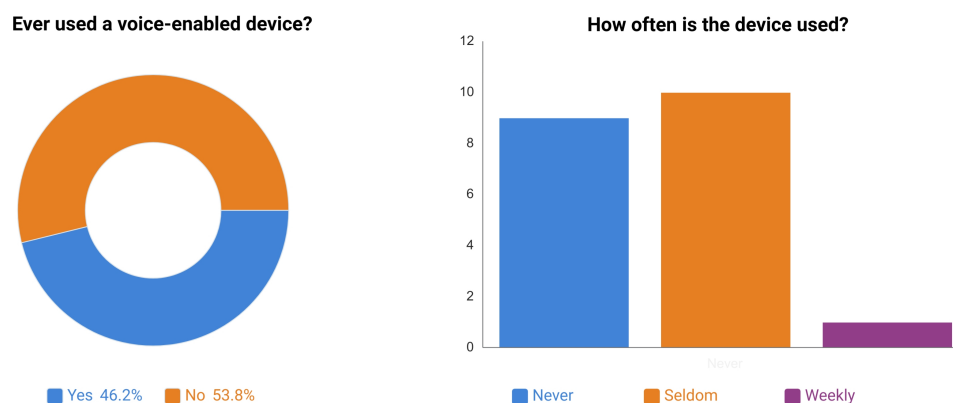


Figure 9. Statistical data deviated from initial survey (Source: own authors' elaboration).

Finally, a feedback survey was designed and given to the students at the end of the course. This survey consisted of one multi-choice question and a second one with dichotomous reply options (yes/no), with three more open-ended questions. We did not implement reliability analysis as the survey aimed to get a qualitative opinion from the students (see Table 4). We gathered answers from 43 students (70.5% from the total amount of participants). The feedback given to us by these students allowed us to better understand their personal experience when interacting with the Alexa skill, as well to collect information on how to further improve it. One of the most interesting outcomes of the survey was to find out that a vast majority of the students (81.4%) would like to receive events through an Alexa-enabled device, but only 6 of the surveyed students (13.9%) did answer they used the Alexa skill to do so (See Figure 10).

Students would like to have more content on the current Alexa skill, which can enable them to get information regarding all their courses (different activities within the course, exam dates, material release dates, essay deadlines, etc.), as well as other information regarding the school, such as upcoming special events (expositions, talks and conferences, etc.). In contrast, the survey indicates that Moodle is seen as a very complete and useful platform as is. Finally, the answers to the survey suggest that students are not as familiarized with voice technology as with other current technologies, as, for example, mobile apps, and voice technology is not yet integrated in their daily lives. This unfamiliarity is reflected in the existence of a certain level of insecurity from the students when it comes to utilizing technology, which in the case of Alexa devices, requires listening to the user continuously in order to activate and initiate the interaction with the user.

Table 4. Feedback survey to students (Extract taken from Saiz-Manzanares et al. [23]).

Survey Question	Possible Answers
What option do you use to know about events from the course?	A—Event’s calendar from Moodle B—Uploaded PDF from the teacher C—Alexa skill D—Ask to other students E—I took notes of the dates given the first day of class
Do you like to receive notifications through Alexa-enabled devices?	Yes No
What additional information would you like to receive through the Alexa skill?	Open answer
What additional information would you like to receive through Moodle platform?	Open answer
If you did not use the Alexa skill, please tell us more about why and give us suggestions for improvement	Open answer

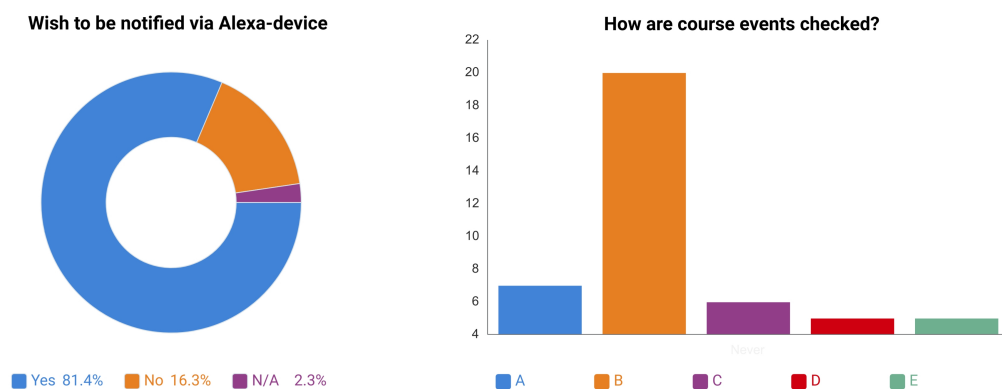


Figure 10. Statistical data deviated from the feedback survey (Source: own authors’ elaboration).

5. Results

Once the usability evaluation was completed, we moved to further investigate the results obtained by the usage of the Alexa skill, and compare such results with the feedback previously gathered from the students. The usage of the skill was relatively low. On February 3rd, the first day of the course, the Alexa skill was introduced to the students. It is during that brief time of introduction (around 15 min) when most of the interaction with the Alexa skill happened. The usage of the Alexa skill during the time of evaluation can be seen on Figure 11. There are some sporadic interactions with the skill during the following days and weeks. However, those sporadic interactions occurred on the same days as the instructor gave in-class reminders about the Alexa skill.

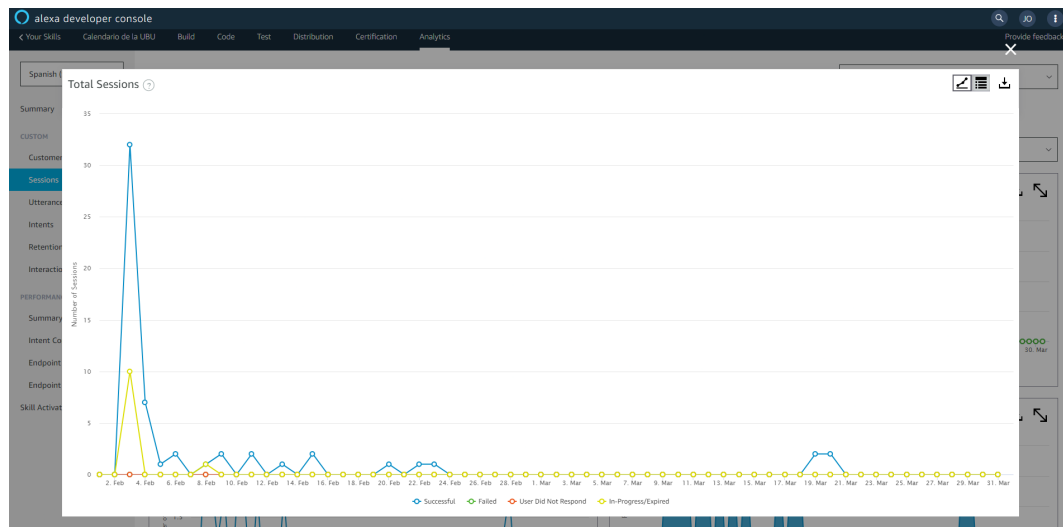


Figure 11. Total sessions opened towards the Alexa skill.

We aimed to investigate if there could be some technical issue that would be affecting the usability experience of the skill. We began by looking at the skill activation and account linking processes. We found out that, while most of the students linked their accounts successfully during the presentation day, all the intents in following days were never completed successfully (see Figure 12). We found no record of error related to the activation or account linking processes on the skill logs, and the Alexa Developer Console did as well concur on the fact that there were no errors to be found. However, the feedback survey did provide us with a possible explanation.

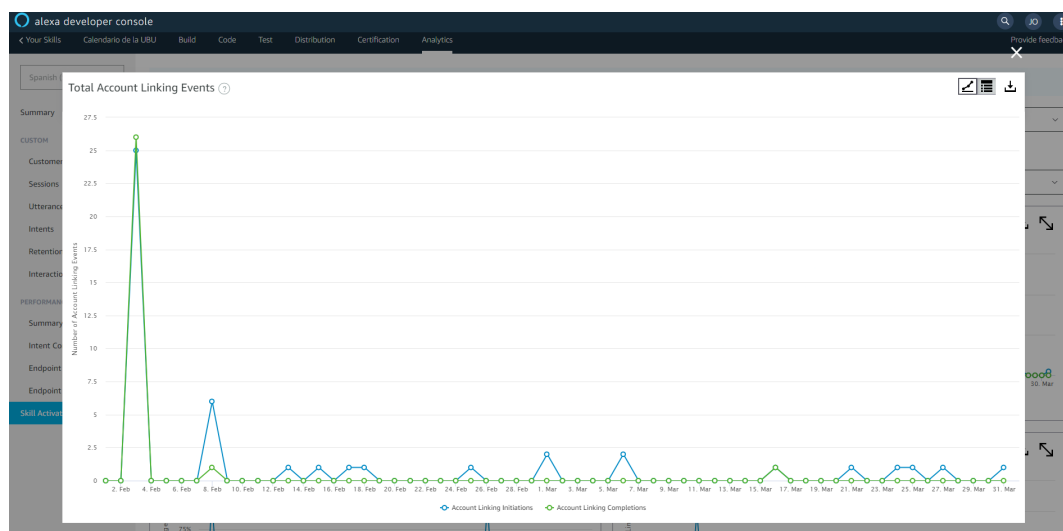


Figure 12. Account Linking data for Alexa skill.

It is worth mentioning that the results of the feedback survey are further detailed and exhaustively analyzed in the works by Saiz-Manzanares et al. [23], where a more profound study on the effectiveness of using IPAs in education is performed. This particular study analyzes what is the students' perception on the usefulness of IPAs when used in conjunction with LMSs, researching if there are significant differences in how students access to information provided by LMSs, as well as if there are significant differences in the students' learning outcomes, depending on use versus non-use of an IPA. From the students' feedback we could deduce that providing access for the skill to their private data located in Moodle might be too much to ask from them in proportion to the gain. They felt the Alexa skill would not provide them with value enough to equal for the potential privacy risks. Additionally, these results match the expected outcome given the participant profiles we defined from the evaluation's initial

survey. More than half the students that participated on the survey had never used a voice-enabled device, with some of them using them seldom, if ever. It would be expected that users would be reluctant to go over an account linking process when they are not comfortable utilizing the device itself as part of their daily routine.

Furthermore, from the feedback survey, we can extract the sense of completeness that Moodle brings to the students. The feedback gained on possible improvements for the skill reflects the expectations from the students for the Alexa skill to be able to operate at the same level as Moodle, providing the same wide range of information related to not only courses but any kind of event regarding the educational day-by-day life of the student. Similar to the activation and account linking processes, we found no evidence of error that might cause users to stop using the skill or which would impact negatively to the experience. As previously mentioned, most of the interactions with the skill happened during the presentation day, with sporadic usages on the same days as the instructor reminded the class about the skill. Once again, based on this insight and the data gathered from the feedback survey, we can resolve that students are not yet familiarized with voice technology and do not feel comfortable as to integrating it on their daily routines.

Easy and fast accessibility to content are highly valued needs for students, and platforms like Moodle already provide a solution for such expectations, to a certain degree, while to really match such expectations, Moodle and voice technology require to attain more elaborated integration capabilities than currently available. Today, Moodle offers powerful tools to gather information from external applications, such as the Moodle Web Services. However, in order to create smooth and realistic interactions between users and Alexa devices, there is a need for a missing layer of interoperability.

As we found during the development process, the information gathered from Moodle via Web Services required to be processed so that Alexa could dictate the sentence in a way that the user could make sense out of it. We were forced to implement this missing layer, which required to hard-code into our application part of the data that would be necessary for the construction of those sentences to be spoken by the Alexa device. As the data had to be hard-coded, only developers were able to influence and modify the resultant outspoken sentence, but people with no software development knowledge, as, for example, some of the course instructors, could not make any changes. While this is a manageable situation when developing a prototype for close-controlled tests, it is not a plausible alternative for a production-ready application. Instructors must be able to manage information within Moodle to create voice-specific content through the same user interfaces used currently to create visual content displayed on the web. Moodle would have to be enhanced with new forms of inputting information for voice-specific matters, in addition to new tools that will allow instructors to pre-listen the outspoken sentences and do the necessary adjustments, prior to publicly releasing such content. It is when the instructor feels comfortable with the tools to create such voice content that the student would receive a gratifying experience when interacting with voice devices, which then would lead to an increase of the interaction with the voice device, and ultimately making the interaction with voice devices an integral part of the user's educational life.

6. Conclusions and Future Work

In this paper, we present the work done to build an Alexa skill for educational purposes, including its integration with Moodle, as response to our research question (RQ1), the development of which takes into consideration the existing scientific knowledge currently available. Our aspiration is to provide new scientific insight to help and guide researchers on future works of similar characteristics by exposing our successes and failures from the decisions and technical implementations taken along the development process.

Contrary to the common approach taken by previous research on the field, we aimed to build our prototype of Alexa skill so that it would be immediately released and publicly accessible, while the current research available provides studies where prototypes are tested under controlled circumstances, mentioning conclusions about the future possibilities of releasing a production-ready version [33,35].

Nevertheless, we carried out a usability evaluation as well, to provide us with insight regarding the usage of the skill. With an initial survey, we were able to create participant profiles for better understanding of the feedback provided by the students in the following surveys and to further comprehend the results gathered from the analytical data extracted from the usage of the skill.

For our research question (RQ2), and contrasting with some of the results we encountered on papers published in recent years, our findings indicate that Moodle is not a platform which currently provides the necessary tools for voice-content creation. Our findings indicate that, in order to create a voice experience with the use of Moodle data, there needs to be a middle layer that would process the data and produce sensible sentences that can be comprehend by users when spoken by a voice device. An alternative to build such missing layer of interoperability would be to implement enhancements that would allow Moodle to be ready for voice-content creation. As future lines of work, our team is considering how such enhancements could be brought to Moodle, either in the form of a Moodle plugin or as an additional application, similar to the Moodle mobile app, but for voice devices. Moreover, creating an additional platform that would bridge the gap between Moodle and voice devices could be an alternative.

Besides voice-content creation, usability can be improved as well, providing a better experience for students when interacting with Moodle via voice instead of traditional visual interfaces. A new line of future work opens for researching how to improve the Moodle platform to be used via voice. A possible path could be to introduce a voice assistant within the Moodle mobile app, or perhaps create new plugins for existing web browsers to interact with Moodle via voice directly from the computer.

Finally, we acknowledge the limitations of our Alexa skill, and we will continue working on functionality improvements in the upcoming developments of the skill. To enhance the limited set of commands understood by the skill, we aim to improve the skill to respond to any inquiry related to a course with no restrictions to what course that might be. Furthermore, the introduction of additional languages is on the scope for improvements. Currently the skill is only available in Spanish, but English could be very helpful for international students. Furthermore, we recognize the need to improve the methodology used when surveying participants regarding the experimentation and usability of innovative technology such as IPAs. For future studies, we perceive employing measurement tools as being beneficial for evaluation, for example, a System Usability Scale (SUS) [46] or User Experience Questionnaire (UEQ) [47].

7. Patents

UBUVoiceAssistant Computer application is registered in the Spanish General Property Registry of the Ministry of Culture and Sports; Registration number: BU-69-20 [48].

Author Contributions: Conceptualization, M.C.S.-M., R.M.-S. and J.O.-O.; methodology, J.O.-O.; software, J.O.-O.; 491 validation, M.C.S.-M., R.M.-S.; formal analysis, M.C.S.-M., R.M.-S.; investigation, M.C.S.-M., R.M.-S. and J.O.-O.; resources, M.C.S.-M., R.M.-S. and J.O.-O.; data curation, M.C.S.-M., R.M.-S.; writing—original draft preparation, 493 J.O.-O.; writing—review and editing, M.C.S.-M., R.M.-S. and J.O.-O.; visualization, J.O.-O.; supervision, M.C.S.-M., 494 R.M.-S.; project administration, M.C.S.-M., R.M.-S. and J.O.-O. All authors have read and agreed to the published version of the manuscript.

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Ethics Statement: The Ethics Committee of the University of Burgos approved this study, N° IR 30/2019. Written informed consent was in each case requested from the students who participated in this research. They all gave their written informed consent in accordance with the Declaration of Helsinki.

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4.3 Article 3: *Using Advanced Learning Technologies with University Students: An Analysis with Machine Learning Techniques*

This article is available at *Electronics* (ISSN 2079–9292), an international, peer-reviewed, open-access journal on the science of electronics and its applications, published semimonthly online by MDPI. It is an open-access journal, free for readers, with article processing charges (APC) paid by authors or their institutions, and it is indexed within Scopus, SCIE (Web of Science), CAPlus/ScFinder, Inspec, and many other databases, with a rapid publication process where manuscripts are peer-reviewed and a first decision is provided to authors approximately 15 days after submission, with acceptance to publication undertaken in 3.7 days.

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Regarding the current status of the article, and based on metric data from *Web of Science*, the paper has no citations and 50 references (see Figure 4.8). As well, from the journal's metric data, it can be found that the article has had 496 views of its abstract and 413 views of the full document since the date of publication (See Figure 4.9).

Publishing Date: October 27th, 2021

Journal Name: Electronics (ISSN 2079–9292)

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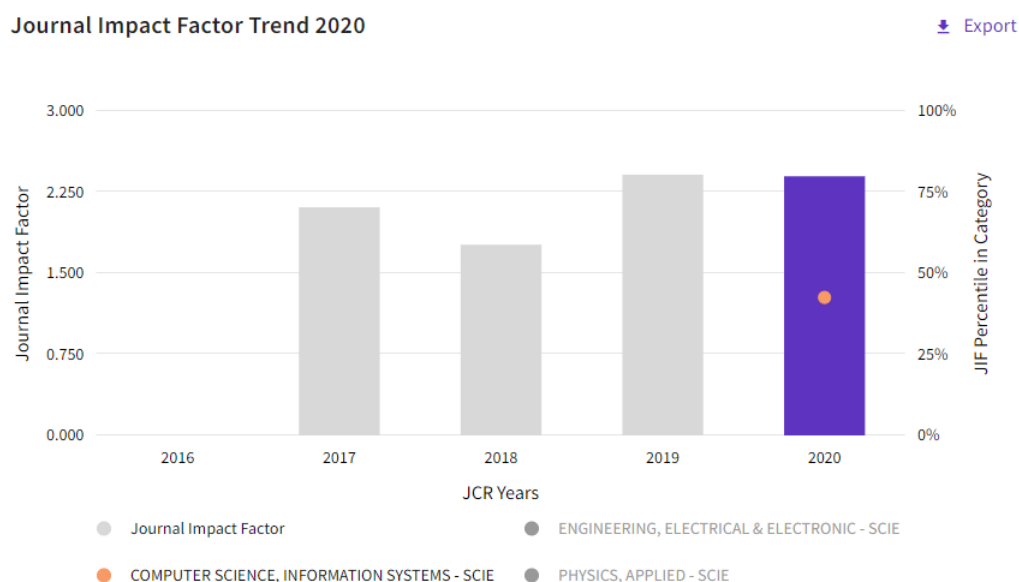


Figure 4.7: Article 3 - Journal Impact Factor 2020. (Source: [99])

Using Advanced Learning Technologies with University Students: An Analysis with Machine Learning Techniques

By: Saiz-Manzanares, MC (Saiz-Manzanares, Maria Consuelo) ¹; Marticorena-Sanchez, R (Marticorena-Sanchez, Raul) ²; Ochoa-Orihuel, J (Ochoa-Orihuel, Javier) ²

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Abstract
The use of advanced learning technologies (ALT) techniques in learning management systems (LMS) allows teachers to enhance self-regulated learning and to carry out the personalized monitoring of their students throughout the teaching-learning process. However, the application of educational data mining (EDM) techniques, such as supervised and unsupervised machine learning, is required to interpret the results of the tracking logs in LMS. The objectives of this work were (1) to determine which of the ALT resources would be the best predictor and the best classifier of learning outcomes, behaviours in LMS, and student satisfaction with teaching; (2) to determine whether the groupings found in the clusters coincide with the students' group of origin. We worked with a sample of third-year students completing Health Sciences degrees. The results indicate that the combination of ALT resources used predict 31% of learning outcomes, behaviours in the LMS, and student satisfaction. In addition, student access to automatic feedback was the best classifier. Finally, the degree of relationship between the source group and the found cluster was medium ($C = 0.61$). It is necessary to include ALT resources and the greater automation of EDM techniques in the LMS to facilitate their use by teachers.

Keywords
Author Keywords: advanced learning technologies; LMS; machine learning; self-regulated learning
Keywords Plus: SYSTEMS

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Figure 4.8: Article 3 - Record from the Web of Science. (Source: [100])

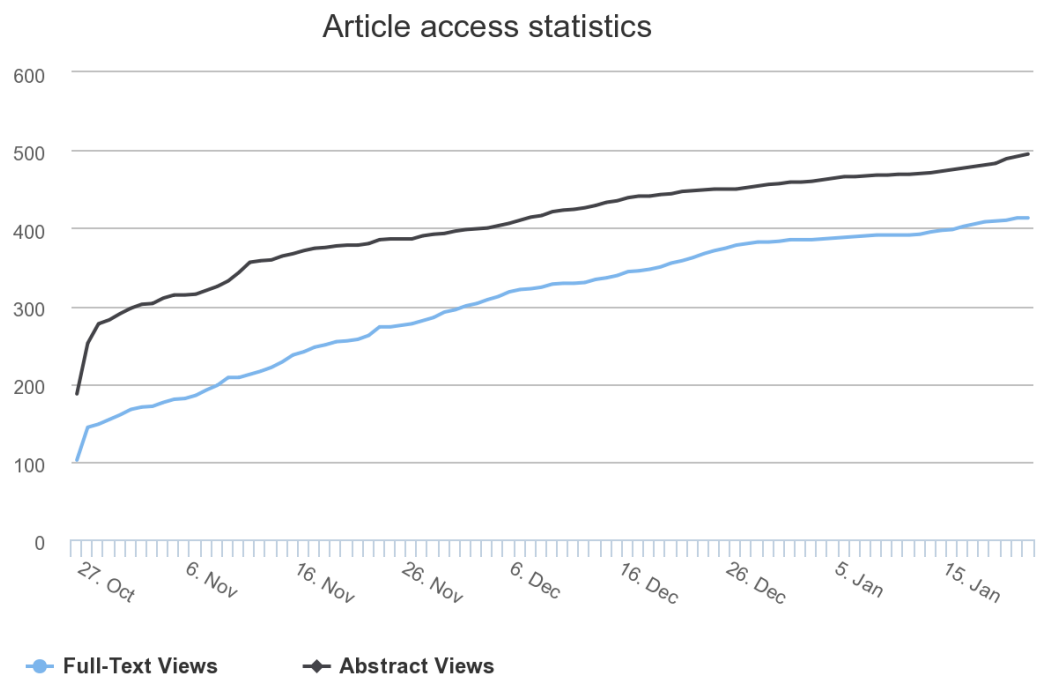


Figure 4.9: Article 3 - Access Statistics. (Source: [101])

Article

Using Advanced Learning Technologies with University Students: An Analysis with Machine Learning Techniques

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Abstract: The use of advanced learning technologies (ALT) techniques in learning management systems (LMS) allows teachers to enhance self-regulated learning and to carry out the personalized monitoring of their students throughout the teaching–learning process. However, the application of educational data mining (EDM) techniques, such as supervised and unsupervised machine learning, is required to interpret the results of the tracking logs in LMS. The objectives of this work were (1) to determine which of the ALT resources would be the best predictor and the best classifier of learning outcomes, behaviours in LMS, and student satisfaction with teaching; (2) to determine whether the groupings found in the clusters coincide with the students’ group of origin. We worked with a sample of third-year students completing Health Sciences degrees. The results indicate that the combination of ALT resources used predict 31% of learning outcomes, behaviours in the LMS, and student satisfaction. In addition, student access to automatic feedback was the best classifier. Finally, the degree of relationship between the source group and the found cluster was medium ($C = 0.61$). It is necessary to include ALT resources and the greater automation of EDM techniques in the LMS to facilitate their use by teachers.

Keywords: advanced learning technologies; LMS; machine learning; self-regulated learning



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1. Introduction

Today’s society is constantly evolving. Technological advances, together with the current COVID-19 crisis, are underlining the need for a change in the teaching–learning process in education. This change is particularly significant in university education. It is centred on the development of instructional modalities, such as e-Learning and Blended Learning (b-Learning). Both implement learning management systems (LMS). These systems can integrate a wide variety of educational tools, such as virtual reality, augmented reality, robotics, artificial intelligence, holograms, virtual laboratories, etc. [1–3]. However, in order to facilitate effective learning in students, these technological tools must be implemented with appropriate pedagogical designs [4,5]. Consequently, university education today faces many challenges, one of which is the integration of technological resources in LMS to improve teaching [6]. Among these methods is the facilitation of self-regulated learning (SRL) through the use of advanced learning technologies (ALTs) in LMS. This will help in providing students with personalised help [7,8], which increases their motivation [9]. In particular, teachers, through the use of different didactic resources (e.g., virtual labs, infographics, flipped learning chatbot experiences, serious games, multimedia resources [10], online project-based learning (OPBL) methodology) [11,12] and intelligent tutoring systems (ITS) [13], can promote individual and group work [14]. In addition, the joint use of ALT and LMS allows the recording of interactions during the teaching–learning process. These records can be analysed with statistical and educational data mining (EDM)

techniques [15]. All of this will allow the teacher to follow the learning trajectory of each of their students [16]. Another advantage is that the use of ALT facilitates SRL in the student in real time [17]. Similarly, the use of ALT in LMS will facilitate collaborative work [18,19]. However, the implementation of these technological resources currently requires constant human supervision. To solve this problem, the implementation of intelligent multi-agents based on natural language is being initiated [20]. The results of their use are promising with respect to improving academic performance and perceived usability in students [21]. Specifically, all ITS have one feature in common: they all provide real-time feedback to the learner, which facilitates the personalisation of learning [17,20]. The use of these resources has shown promise [22], because they enhance dynamic scaffolding, which can help students learn more effectively. Such systems are highly interactive and employ artificial intelligence, and some of them can be easily integrated into LMS. However, they require the teacher to have digital skills and the ability to use EDM techniques (supervised and unsupervised learning). This aspect could slow down their implementation in educational contexts [23]. However, the use of these systems has more advantages than disadvantages; for example, the use of Intelligent Personal Assistants (IPAs) seems to improve students' listening and speaking skills without the presence of a physical teacher [24]. In addition, the use of other ITS resources seems to facilitate students' access to LMS and their motivation towards learning [8]. This promotes self-reflection on their own practice, which enhances the acquisition of new concepts and problem solving [25]. However, as discussed above, digital competencies are required for successful use [26]. This poses a challenge for academic leaders in universities when trying to promote the training of teaching staff in this area [27].

In particular, this training plan should focus on the use of IPAs, as their future in the educational field is promising [28]. The advantages of IPAs compared to other ITS are that they establish conversational empathy with the user [29] and are highly useful with students with special educational needs (e.g., people with visual impairments or attention deficits) [30]. Additionally, IPAs provide learners with web navigation aids, which enhance the personalisation of learning [31,32]. However, IPAs should be adapted to the requirements of each task, and not have a generalised structure [33]. Researchers also stress the need for more research in this area [34]. Another aspect that should be included in university teacher training is the use and interpretation of EDM techniques [35], specifically those related to supervised predictive and unsupervised clustering learning techniques [36]. Through these techniques, it is possible to determine the learning patterns of students and detect students at academic risk [37]. These data will provide the teacher with information helping them to give personalised education to a student or group of students with similar characteristics.

In conclusion, many educators do not feel qualified to use these technologies independently, due to the difficulties of applying ALT in LMS and the absence of machine learning techniques useful for the interpretation of the findings. Figure 1 shows a summary of the preceding, and Table 1 presents the benefits and challenges of digitalization in the teaching–learning process.

The world is becoming increasingly digital, indicating the need for a number of changes in teaching design and the usage of educational resources in university teaching. Experts recommend establishing a Smart University with technology-based pedagogy [38]. The research should be focused on evaluating the efficacy of these technological resources at various levels and with different types of students. In this regard, the European Agenda 2030 [39] includes objectives to achieve quality education, such as increasing digital competences and promoting equal opportunities via the development of sustainable and inclusive quality education [40].

As the use of these resources in education is still an emerging field, with few empirical studies rigorously analysing their impact on student learning outcomes, more research is needed [20].

Based on the above state of the art, the research objectives of this study were:

- RO1. To find out whether the combination of ALT resources predicts students' satisfaction and behaviours in the LMS;
- RO2. To find out which is the best cluster with respect to student satisfaction and behaviour in the LMS;
- RO3. To find out whether different clusters are related to the ALT resources used in the different intervention groups.

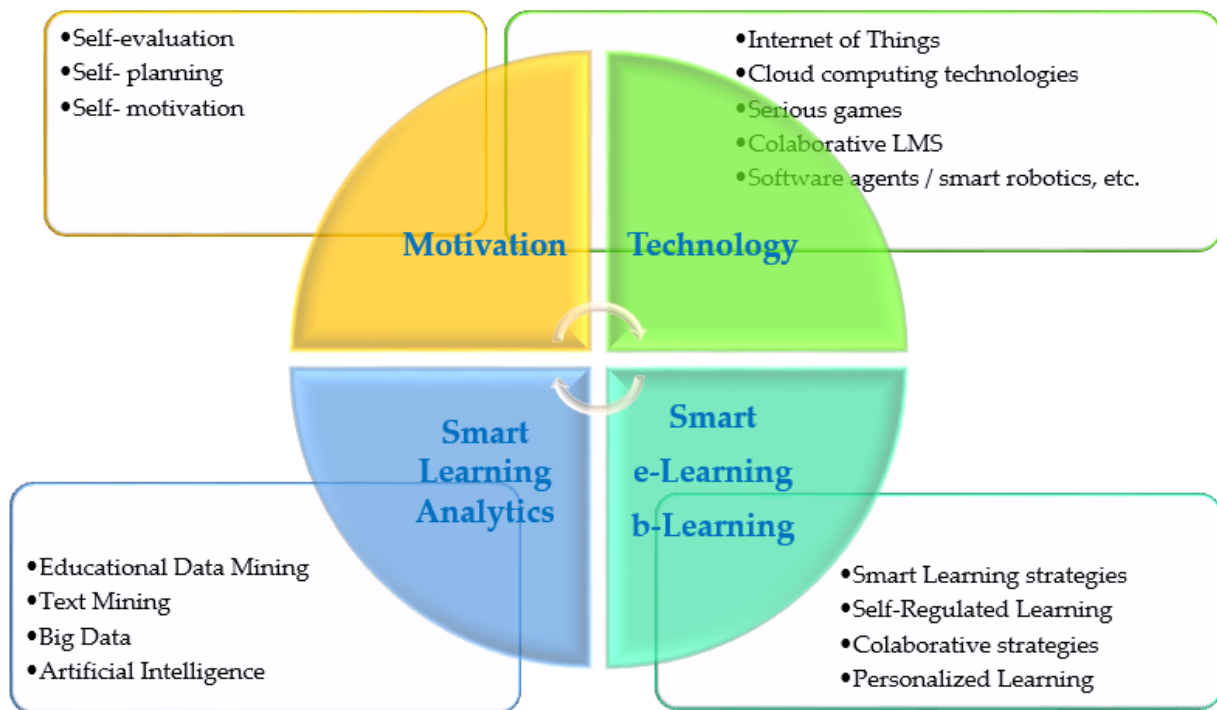


Figure 1. Teaching-learning process in 21st century society.

Table 1. Summary of the benefits and drawbacks when using digital resources in the teaching–learning process.

Resources	Advantages		Challenges	
	Students	Teachers	Students	Teachers
ALT	Personalized help Easy to get personalized feedback in real time	Make it simpler to figure out how a learner learns Aid students based on their requirements Personalise teaching Simplify the creation of automated personalised teaching Feedback processes	They require certain knowledge of, as well as the need for, skills on the application of LMS	Training in digital skills and EDM is required
LMS	Personalise learning Increase motivation Individual work Group work Use different didactic resources	Personalise teaching Enhance individual and group work Include didactic resources		
ATL and LMS		Enables the recording of interactions (logs)		

Table 1. Cont.

Resources	Advantages		Challenges	
	Students	Teachers	Students	Teachers
EDM		Know students' learning patterns Easy to find out which of the resources implemented is more effective in increasing the learning results in the students Simplifies groupings of students to offer educational answers adjusted to each of them		
ITS	Personalised learning Increased motivation	Make it easy to design personalised automatic feedback processes		
IPA and chatbot	Facilitate attention to diversity and help students with special educational needs Enhance personalised learning Facilitate an increase in motivation	Facilitate the educational response in students with special educational needs		
All of the above	Promote the use of metacognitive self-assessment strategies in students Facilitate effective learning	Increase constructive and meaningful learning in students Increase learning outcomes	They require certain knowledge of, well as the need for, skills related to multiple digital resources	They involve teaching with active digital methodologies

2. Materials and Methods

2.1. Participants

Over the course of two academic years, we worked with 225 third-year Health Sciences students in two subjects. Both tests were conducted during the COVID-19 pandemic (academic years 2019–2020 and 2020–2021), with 98 students from the Occupational Therapy program and 127 students from the Nursing program (see Table 2). The sample was chosen via convenience sampling.

Table 2. Descriptive statistics for the sample of participants.

Group	Subject	Health Sciences Students (N = 225)							Rate of Return Degree	Subject Performance Rate
		N	n	Men		n	Women			
				Mage	SDage		Mage	SDage		
Group 1	Subject 1	46	8	21.63	1.77	38	22.42	2.25	90.24%	100%
Group 2	Subject 2	61	5	21.40	0.89	56	23.54	6.30	95.83%	100%
Group 3	Subject 1	52	7	21.57	0.79	45	22.64	4.72	90.14%	100%
Group 4	Subject 2	66	7	25.71	7.39	59	23.44	5.51	96.83%	100%

Note. Group 1 = students from the Occupational Therapy course, academic year 2019–2020; Group 2 = students from the Nursing course, academic year 2019–2020; Group 3 = students from the Occupational Therapy course, academic year 2020–2021; Group 4 = students from the Nursing course, academic year 2020–2021. Performance rate: percentage ratio between the number of credits passed by the total number of students enrolled in a given academic year with respect to the number of credits enrolled by these students in the same year. Source: University of Burgos Information System.

2.2. Instruments

1. Learning Management System-LMS-. We use a LMS based on Moodle v.3.9: Virtual Learning Platform from the University of Burgos, UBUVirtual.
2. Online Project-Based Learning (OPBL). All student groups worked with the OPBL methodology in small groups (3 to 5 members).
3. Virtual laboratories. Ad-hoc-oriented and open access in the Repository of the University of Burgos. SRL methodology was used for all of them [41,42].
4. Quiz-type questionnaires with process-oriented feedback. The learning check questionnaires included multiple-choice (four options) questions with one correct option. All of them included automatic process-oriented feedback, in which the student was given information about the correct answer, the reason for it, and where they could find the theoretical justification within the material given.
5. Intelligent Personal Assistants-IPA- Students could access the main dates of the course (delivery of practices, completion of questionnaires, project delivery, etc.) using the Amazon Alexa application (mobile, tablet, or computer). Amazon Alexa skills were developed and deployed via the Amazon Web Service (AWS). Students first had to prove their identity to be able to use this application. This process was initiated via UBUVirtual, the learning platform (LMS) of the University of Burgos. To access the Alexa resource, students had to provide valid credentials of their identity within the LMS. Students could then utilize the skill without needing to access the LMS again after the first successful validation. As a result, the connection was secure, and personal data were secured [43,44]. During the academic year 2019–2020, the device was used with Group 1 of students from the Occupational Therapy degree.
6. Flipped classroom experiences. Flipped classroom classes were carried out in the four intervention groups. These included the creation of videos based on the topics' thematic units, with three lessons applied in each of the four intervention groups. After each lesson, students could take a quiz-type questionnaire with process-oriented feedback (see point 4).
7. Gamification with feedback on the results. H5P, featuring in the most recent versions of Moodle, was used to create the gamification activities. The following games were used: crossword, find the words, memory game, speak the words set, and true/false questions. All these activities included process-oriented feedback and a progress bar. They were also divided into three levels of difficulty (beginner, intermediate, and advanced). The gamification activities in both degrees (Occupational Therapy and Nursing) were performed during the final four weeks of the academic year 2020–2021.
8. Laboratory simulation. The simulation practices were designed at the simulation laboratory of the Faculty of Health Sciences from the University of Burgos. This facility has rooms with a Gesell Chamber-type one-way mirror, wherein students can perform simulations with dummies in clinical practice environments. An example of the procedure is available at <https://youtu.be/C8XGemeBuOM> (access on 26 October 2021) which was provided to students from the Occupational Therapy and Nursing degrees during the 2020–2021 academic year.
9. Survey of general satisfaction with the training activity [45]. An ad hoc survey with 19 closed-ended questions assessed on a Likert-type scale of 1 to 5 (1, do not agree at all; 5, strongly agree) and three open-ended questions related to strengths, weaknesses, and proposals for improvement. In this study, the survey had a Cronbach's reliability coefficient of $\alpha = 0.93$ (see Appendix A Table A1).
10. Learning outcomes, measured on a scale of 0 to 10. This measurement considered the work done by students using a project-based learning approach. In the final grade, the elaboration of the project was allocated a weight of 25%, and the defence of the project a weight of 20%. A test with multiple choice questions and a single correct answer was also employed, accounting for 30% of the overall weight. Finally, participation in co-evaluation activities was given 15% of the weight (comprising responses to

questionnaires on the evolution of the teaching–learning process). In each group, the same percentages were used.

11. Plugin “eOrientation” [46,47]. This Moodle plugin was developed as part of a research project funded by the Junta de Castilla y León (Spain). This plugin can be used to collect data related to personalised access to the pedagogical resources utilized by students in each topic over the course of an academic year. It also allows the teacher to communicate with each student individually via email, so as to provide feedback on the results of the learning process. Furthermore, the logs can be exported in multiple file formats (.csv, .xlsx, HTML table, .json, .ods, and .pdf).

2.3. Procedure

Prior to the beginning of this study, a positive report was obtained from the Bioethics Committee of the University of Burgos (No. IR 30/2019), as was the written informed commitment of all research participants. During the second semesters of both academic years, we worked with four groups of third-year students undertaking Health Sciences degrees (Degree in Occupational Therapy and Degree in Nursing). The first academic year (2019–2020) coincided with the COVID-19’s confinement period, hence the teaching had to be virtual, and was conducted via e-Learning. The second course (2020–2021) used a blended learning approach, with in-person course activities and virtual theoretical classes. All of the groups used the same set of methodological resources: OPBL, quiz-type surveys with process-oriented feedback (in some cases for the teacher’s evaluation of knowledge and in others for the student’s self-evaluation of knowledge), and flipped classroom experiences. In addition, depending on the group, various teaching resources were used (virtual laboratories, IPA, gamification with feedback on the results, and laboratory simulation [48]). A convenience sampling method was applied for the distribution of the groups. The “eOrientation” tool [47] was also used to keep track of the students’ learning progress in the LMS. Table 3 shows a summary of the resources applied in each category.

Table 3. Teaching methodology applied in the intervention groups.

Teaching Methodology with ALT	Group 1	Group 2	Group 3	Group 4
e-Learning	Yes	Yes	No	No
b-Learning	No	No	Yes	Yes
OPBL	Yes	Yes	Yes	Yes
Virtual laboratories	Yes	No	Yes	No
Quiz-like questionnaires with feedback oriented to the evaluation processes	Yes	No	Yes	No
IPA	Yes	No	No	No
Flipped classroom experiences	Yes	Yes	Yes	Yes
Quiz-type questionnaires with feedback oriented to the self-evaluation processes	No	Yes	No	Yes
Gamification with feedback on results	No	No	Yes	Yes
Laboratory simulation	No	No	Yes	Yes

2.4. Research Design

A descriptive-correlational design was used [49] and the factors applied were: teaching methodology in LMS (e-Learning vs. b-Learning); use of IPA vs. non-use; use of gamification vs. non-use; use of laboratory simulation vs. non-use. The analyses were performed with the statistical package SPSS v.24 [50].

2.5. Data Analysis

To test RO1, the supervised learning techniques of regression (multiple linear regression) were applied. To test RO2, the supervised learning techniques of classification (CHAID decision tree and k-nearest neighbour, or *k*-nn) were applied. To check RO3, unsupervised learning techniques (*k*-means) were applied.

3. Results

3.1. Contrasting RO1

To test RO1, supervised learning regression techniques were used to study the degree of prediction of learning outcomes and student satisfaction with the ALT resource combinations used. An $R^2 = 0.31$ was found, indicating that student group type explains 31% of student learning outcomes. Specifically, group type predicts learning outcomes at 26.1%, access to automatic feedback from different resources at 28%, access to the LMS at 23%, and student satisfaction at 14%, all parameters being significant at 95%. The tolerance indicators were not close to 0, so the independent variables were not considered redundant, and none had to be eliminated with respect to the dependent variable (type of group). Likewise, the VIF values were no greater than 10, meaning they were within the fit values (1–10) (see Table A1). In the collinearity analysis, dimension 2 obtained a variance proportion of 0.92 with respect to accesses to automated feedback, while dimension 3 obtained a variance proportion of 0.91 with respect to the accesses to the LMS (See Table A2).

3.2. Contrasting RO2

For RO2, supervised classification learning was applied—specifically, the CHAID decision tree algorithm. The dependent variable was the type of group and the independent variables were learning outcomes, access to automatic feedback from different resources, access to the LMS, and student satisfaction with teaching. Cross-validation was applied. (This makes it possible to evaluate the robustness of the tree structure. Cross-validation divides the sample into a subsample number, followed by the creation of tree models that do not include the data for each subsample. In SPSS, the first tree is based on all cases except those corresponding to the first fold of the sample; the second tree is based on all cases except those of the second fold of the sample, and so on. For each tree, the risk of misclassification is calculated by applying the tree to the subsample that was excluded when it was first created. A maximum of 25 sample folds can be specified. The higher the value, the lower the number of cases excluded from each tree model. Cross-validation generates a single, final tree model. Cross-validation risk for the final tree is calculated as an average of the risks of all trees. Specifically, in this study, the fold cross-validation used was 10). The ranking variable was access to automatic feedback from different resources, isolating three nodes (see Figure 2). In the lowest node (values below 127.0), 67.2% are members of Group 1. In the intermediate node (values between 127.0 and 202.0), 63.2% are members of Group 4, and in node 3 (values higher than 202.0), 61.1% are members of Group 2. Therefore, it can be inferred that access to automatic feedback was the independent variable with the greatest effect on the differences between the types of group, and the group in which the best results were obtained in this variable was Group 2 (in which the following ALT resources were applied: e-Learning, OPBL, quiz-type questionnaires with process-oriented feedback, and flipped classroom experiences). The group that obtained intermediate results was Group 4 (in which the following ALT resources were applied: b-Learning, OPBL, virtual laboratories, quizzes with feedback oriented towards self-assessment processes, gamification with feedback on the results, and laboratory simulation). Finally, the group that registered a higher percentage in the lower node was Group 1 (in which the following resources were applied: ALT e-Learning, OPBL, virtual laboratories, quizzes with process-oriented feedback, and IPA) (see Figure 2).

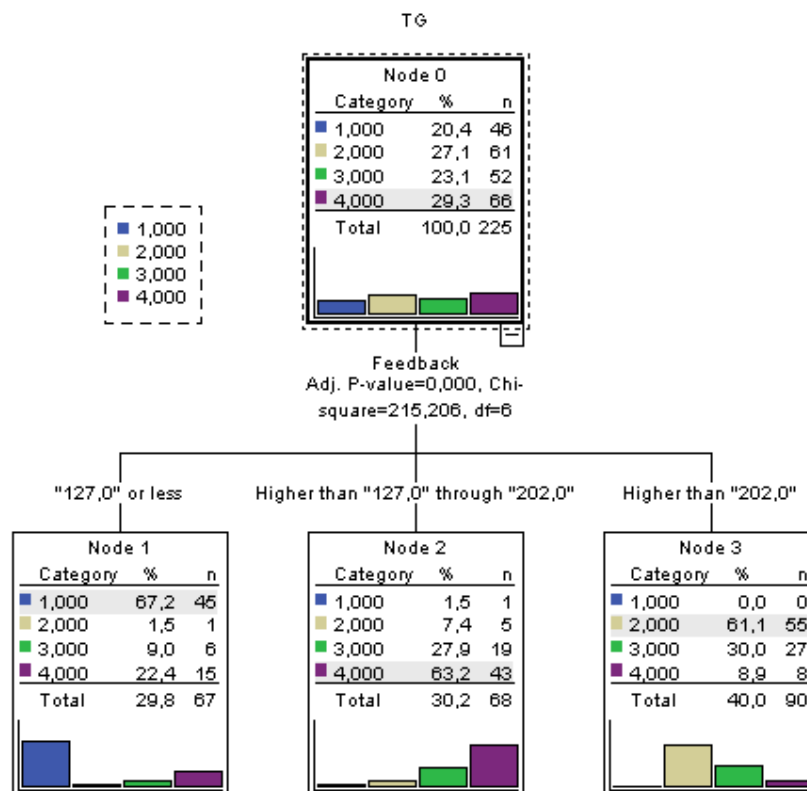


Figure 2. Decision tree on the effectiveness of combinations of ALT resources in LMS.

Combination of ALT resources used: Group 1—e-Learning, OPBL, virtual laboratories, quiz-type questionnaires with process-oriented feedback, IPA, flipped classroom experiences; Group 2—e-Learning, OPBL, quiz-type questionnaires with process-oriented feedback on self-assessment, flipped classroom experiences; Group 3—b-Learning, OPBL, virtual laboratories, quiz-like questionnaires with process-oriented feedback, flipped classroom experiences, gamification with feedback on results, laboratory simulation; Group 4—b-Learning, OPBL, quiz-like questionnaires with process-oriented feedback on self-assessment, flipped classroom experiences, gamification with feedback on results, laboratory simulation.

The k -nn algorithm was also applied, where the focal case identifier used was the type of group. The features were learning outcomes, access to automatic feedback from different resources, access to the LMS, and student satisfaction with teaching. Four predictors were applied, of which three were isolated: access to automatic feedback from different resources, learning outcomes, and access to the LMS (see Figure 3). Regarding the focal analysis of the features, a greater dispersion was found in the learning outcomes and in the students' satisfaction with teaching (see Figure 3).

The focal analysis highlights cases of particular interest by displaying the k closest neighbours in a graph of space of attributes, homologues, and quadrants, as well as the distances between them. Regarding the features, a greater dispersion was found in the learning outcomes and in the students' satisfaction with the teaching (see Figure 4).

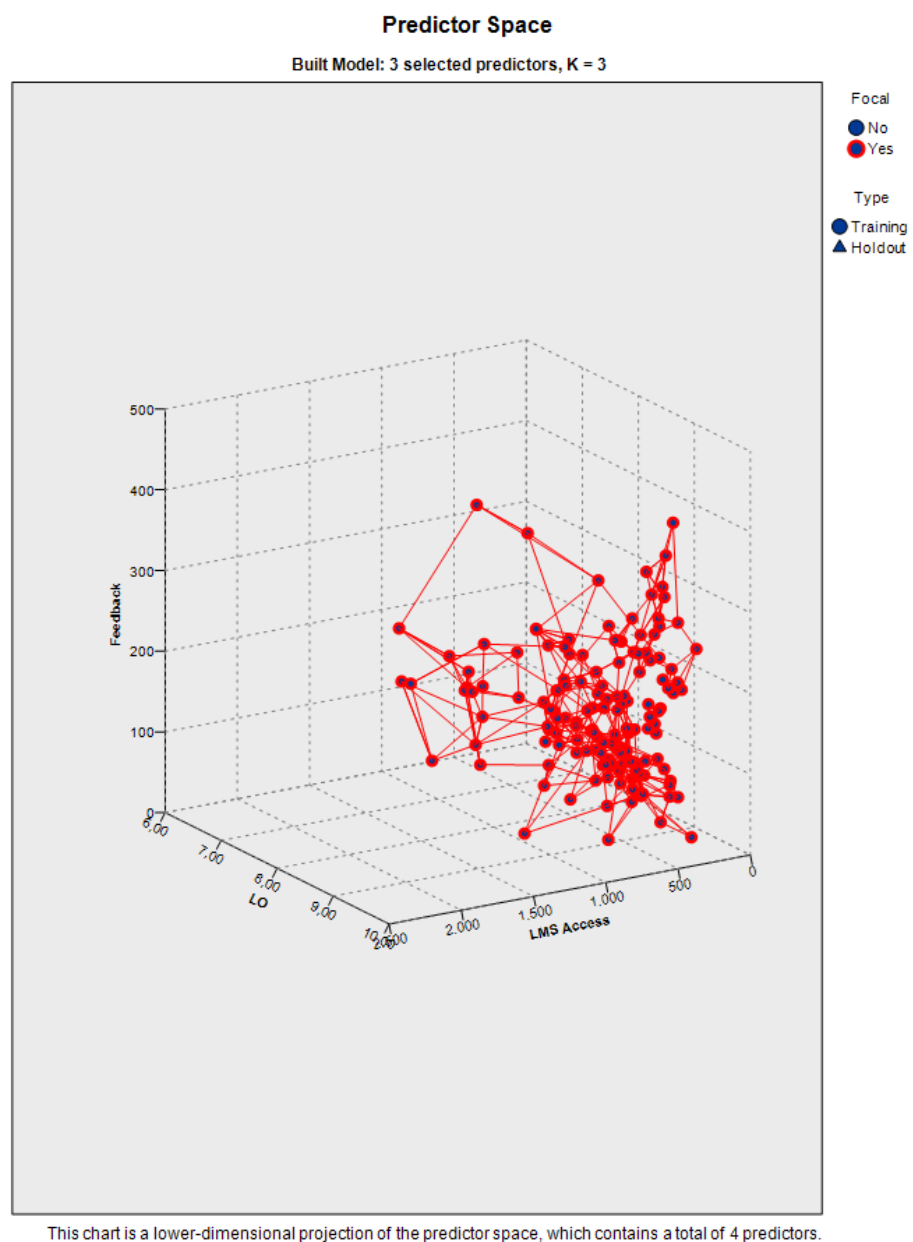


Figure 3. k -nn considering as focal variables the group type (ALT resource combination) and feature selection.

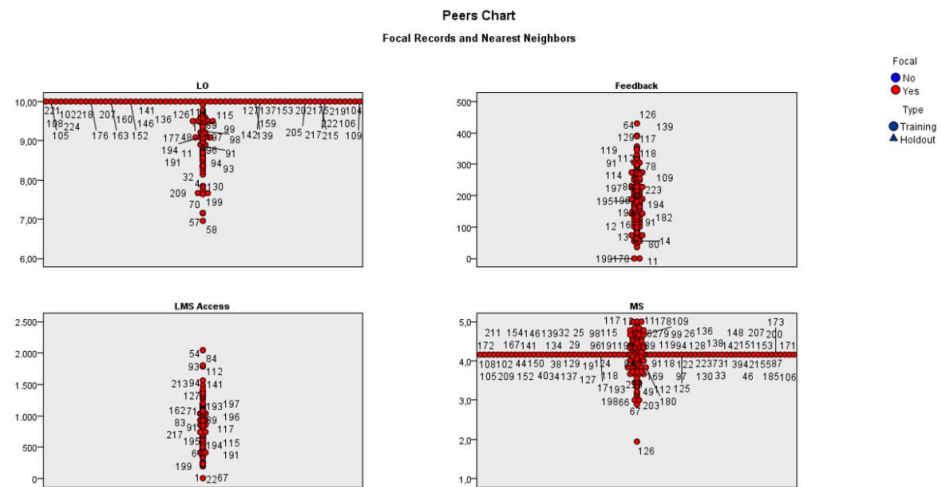


Figure 4. *k-nn* focal analysis of LO, feedback, LMS access, and student satisfaction. Note: LO = learning outcomes; feedback = access to automatic feedback resources; MS = mean student satisfaction with teaching.

3.3. Contrasting RO3

Finally, to contrast the RO3, unsupervised learning clustering techniques were applied, and specifically the *k-means* algorithm was used. Four clusters were found. Cluster 2 included the students with the best learning results; with greater access to automatic feedback and with higher averages of satisfaction with the teaching process, it was considered an *Excellent* cluster. Cluster 4 included students with greater access to the LMS, and showed greater access to automatic feedback and the second-best learning outcomes after the students in cluster 2, and was therefore considered a *Very Good* cluster. Cluster 3 included students with high values for access to the LMS, but lower values of LO, feedback and MS, so it was considered a *Good* cluster, and cluster 1 was the cluster with the lowest values in all variables, so it was considered a *Low* cluster (see Table 4). Next, a cross table was constructed between participants' assignments to the clusters and the groups to which they belonged. A contingency coefficient $C = 0.61$, significant at 95% $p = 0.000$, was found, indicating a medium degree of coincidence in the relationships (see Table 5).

Table 4. Centres of final clusters for the variables LO, feedback, LMS access, and MS.

	Cluster 1 (Low) n = 51	Cluster 2 (Excellent) n = 79	Cluster 3 (Good) n = 77	Cluster 4 (Very Good) n = 18
LO	8.36	10.00	8.67	9.21
Feedback	63	333	171	255
LMS access	8	668	1338	2045
MS	3.0	4.2	4.2	3.7

Note. LO = learning outcomes; feedback = accesses to automatic feedback resources; MS = mean student satisfaction with teaching.

It was found that 64.71% of the members of the low cluster belonged to Group 1 (in which the following resources were applied: e-Learning, OPBL, virtual laboratories, quiz-type questionnaires with process-oriented feedback, and IPA), representing 71.74% of the total group. Likewise, 50.65% of the members of the good cluster (which applied b-Learning, OPBL, virtual laboratories, quiz-type questionnaires with process-oriented feedback, gamification with feedback on the results, and laboratory simulation) belonged to Group 4, which represented 59.10% of the total group. Regarding the very good cluster, 66.66% of the members belonged to Group 3 (b-Learning, OPBL, virtual laboratories, quizzes with process-oriented feedback, flipped classroom experiences, and gamification

with feedback on results), and this in turn accounted for 23.08% of the total group. Finally, 50.43% of the members of the excellent cluster were members of Group 2 (e-Learning, OPBL, quiz-type questionnaires with feedback oriented to self-assessment processes, and flipped classroom experiences), which represented 70.49% of the total group. In addition, significant differences between the clusters with respect to the variables studied were found (see Table A3).

Table 5. Percentage of membership for each intervention group with respect to each cluster.

	Cluster Under n = 51	%	Cluster Excellent n = 79	%	Cluster Well n = 77	%	Cluster Very Good n = 18	%
Group 1 (n = 46)	33	71.74	5	10.87	8	17.39	0	0
Group 2 (n = 61)	5	8.20	43	70.49	11	18.03	2	3.28
Group 3 (n = 52)	6	11.54	15	28.85	19	23.08	12	23.08
Group 4 (n = 66)	7	10.61	16	24.24	39	59.10	4	6.06

Note. Combinations of ALT resources used—Group 1: e-Learning, OPBL, virtual laboratories, quiz-type questionnaires with process-oriented feedback, IPA, flipped classroom experiences; Group 2—e-Learning, OPBL, quiz-type questionnaires with process-oriented feedback on self-assessment, flipped classroom experiences; Group 3—b-Learning, OPBL, virtual laboratories, quiz-like questionnaires with process-oriented feedback, flipped classroom experiences, gamification with feedback on results, laboratory simulation; Group 4—b-Learning, OPBL, quiz-like questionnaires with process-oriented feedback on self-assessment, flipped classroom experiences, gamification with feedback on results, laboratory simulation.

4. Discussion

The type of ALT used in the four groups predicted learning outcomes, access to automatic feedback, access to the LMS, and student satisfaction at 31%. The highest partial prediction was detected in the variable accesses to automatic feedback (28%), followed by the variable learning outcomes (26.1%) and accesses to the LMS (23%), and to a lesser extent in student satisfaction with teaching (14%). The access to automatic feedback was the methodological resource based on ALT that had the highest classification weight in the decision tree algorithm, and the highest percentage of students in this node corresponded to Group 2, in which the following ALT resources were applied: e-Learning, OPBL, quiz-type questionnaires with feedback oriented to self-assessment processes, and flipped classroom experiences. Regarding the application of the *k-nn* algorithm, the variables with the most weight for the classification were access to automatic feedback, learning outcomes, and access to LMS, with a greater dispersion of participants in terms of learning outcomes and satisfaction with teaching. These results seem to indicate that there is a difference in the responses to and effectiveness of the ALT resources applied, depending on whether the teaching is carried out in an e-Learning or a b-Learning modality. This is an important fact for future research, as analysing which ALT resources are the most effective in each teaching modality will guide teachers in their future use under each of these modalities. In addition, these results help with research regarding latent variables that occur, especially in the fields of b-Learning teaching, because we also assessed face-to-face teaching, wherein there may be latent variables that influence learning behaviours, learning outcomes, and student satisfaction. For such reasons, these aspects will be analysed further in subsequent studies.

We did not find a cluster that contained all the highest values in all the dependent variables, although the cluster that came closest, the *Excellent* one, gathered the highest values in the variables of learning outcomes, access to automatic feedback, and average satisfaction with teaching, in which 35.11% of all participants were located. In this cluster, 50.43% were members of Group 2, in which e-Learning teaching was applied with the implementation of the following ALT resources: e-Learning, OPBL, quiz-type questionnaires with feedback oriented to self-assessment processes, and flipped classroom experiences. The percentage of the total members of Cluster 2 was 70.49%. Likewise, in the next cluster, the *Very Good* cluster, the highest values were detected in access to the LMS, but a lower degree of student satisfaction with teaching was found (3.7 out of 5). In this cluster, the highest percentage of students (66.6%) belonged to Group 3, which used the following ALT

resources: b-Learning, OPBL, virtual laboratories, quizzes with process-oriented feedback, flipped classroom experiences, and gamification with feedback on results. However, this only corresponded to 23.08% of the total members of Group 3, which indicates that there was greater homogeneity in the *Excellent* cluster. In summary, it seems that the most important aspects regarding the achievement of better academic results are related to the use of ALT resources that offer automatic feedback on the processes regarding the students' learning responses, which in turn is related to a higher satisfaction of the students with the teaching–learning process. In contrast, greater access to the LMS is not related to better learning outcomes or greater student satisfaction. These differences can be explained by the type of teaching modality; in the first case, an e-Learning modality was used, and in the second a b-Learning modality. In addition, it is necessary to consider that the time of teaching in the first case coincided with the most restrictive period of the pandemic, which necessarily implied strict confinement, and in the second case the teaching was not subjected to strict confinement except in cases of SARS-CoV-2 positivity. This fact may be related to student perceptions of distress or anxiety about the health situation [43]. In the first case, there was no choice of teaching modality, so offering students the option to continue teaching through ALT media allowed for continuing their learning in a context as close to “normality” as possible. This fact could have produced in them a more positive attitude towards the teaching modality. Thus, this circumstance did not occur in Group 1 students who experienced the same situation. Consequently, other variables such as the type of degree may be influential, since Group 1 was formed of Occupational Therapy students and Group 2 of students from Nursing. Furthermore, these results were not repeated during the 2020–2021 academic year in Group 3 (students of Occupational Therapy) or Group 4 (students of Nursing), in which other ALT resources, such as gamification and simulation in the laboratory, had also been implemented.

Finally, it should be noted that although the results are not homogeneous in all groups, the use of ALT resources is effective on the academic performance of students with respect to the combinations of these resources applied, since the performance rate in all groups was 100% compared to the general rates of these groups in the degree (Table 1). The difference in percentage points was 9.76 for Group 1, 4.17 for Group 2, 3.17 for Group 3, and 8.86 for Group 4, which are important values to consider, as they concern the same students in different subjects—those who experienced a pedagogical design based on ALT vs. those who did not.

5. Conclusions

The variability in the intrinsic and extrinsic characteristics of students, which can influence their learning process, makes it difficult to generalize conclusions. In addition, the comparison between the e-Learning and b-Learning teaching modalities is also an important variable. It is therefore difficult to conclude which are the best ALT resources, or combinations of them, to apply in the context of teaching–learning in virtual environments. This variability is related to the motivation of the students with respect to the learning resource, to the moment in which the teaching takes place, and to the teaching modality. In this study, we worked in a pandemic context, which may have caused anxiety in students—not towards the subject or the ALT resources, but towards the uncertainty about their life and future [43,48]. However, the presence of a large number of resources that apply ALT does not ensure better academic results or greater satisfaction. The resources that have been shown to be most effective are those that contain automatic process-oriented feedback [11,27]. Their use seems to be directly related to better learning outcomes and higher student satisfaction [11,27]. As a result, researching the development of automatic feedback using ALT resources is both a challenge and an area requiring continuous focus in this field. Moreover, the use of IPA has not been shown to be highly effective, a possible reason being that it only guides students in very basic issues related to their calendar of events. The use of an IPA in which automatic feedback actions can be applied on the learning processes would probably improve these results. However, since it involves

advanced artificial intelligence technology, implementing this capability in LMS is difficult and still in its early stages of development [20,21,28,31]. It should also be emphasized that using ALT materials improves students' performance rates. Although we are still at the beginning of our journey toward teaching with digital resources, and it is difficult to say which of these resources is the best (as this depends on a variety of factors, such as the context and the characteristics of the students), it appears that their use actually enables better performance.

Because we worked with a convenience sample of students within a certain field of knowledge, Health Sciences, the outcomes of this study should be interpreted with caution. Students in this field are also more likely to have a higher level of vocational motivation for their future career. Future research will look into the impacts of multiple types of ALT on learners at different levels and within different disciplines.

In short, in the digital society of the 21st century, the use of ALT resources for teaching still has a long way to go, and requires substantial research, in terms of both promoting the technology and analysing how its application can improve student learning outcomes. Using resources alone does not guarantee better learning outcomes or motivation. Academic managers confront numerous obstacles when addressing this challenge [27], the first of which is the development of ALT resources within the LMS that are simple for teachers to use. Currently, using these tools requires medium–high-level digital abilities, which most teachers lack. In addition, the interpretation of the results on effectiveness requires the use of EDM techniques that are often not included in the LMS. For this reason, if educators want to learn about the behavioural patterns of the students regarding the use of ALT resources [8,37], they may need to be well-versed in the use of EDM techniques [26]. This is a new obstacle to the effective use of technology aimed at personalized learning [11].

To this end, there is a pressing need to address all these challenges in an increasingly digital teaching–learning context, as well to achieve the goals of the 2030 Agenda [39].

6. Patents

Ochoa-Orihuel, J., Marticorena-Sánchez, R., Sáiz-Manzanares, M.C. UBU Voice Assistant Computer application N° 00/2020/2502; General Registry of Intellectual Property: Madrid, Spain, 29 July 2020 [44].

Sáiz-Manzanares, M.C., Marticorena-Sánchez, R., et al. eOrientation Computer Software for Moodle. Detection of the student at academic risk at University No. 00/2020/588; General Registry of Intellectual Property: Madrid, Spain, 16 January 2020 [47].

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Appendix A

Table A1. Coefficients in the prediction of type of group (combining ALT resources) with LO, feedback, LMS access, and MS.

	Unstandardized Coefficients		Standardized Coefficients	t	p	95.0% Confidence Interval for B		Correlations			Collinearity Statistics	
	B	SE	Beta			Lower Bound	Upper Bound	Zero-Order	Partial	Part	Tolerance	VIF
(Constant)	2.49	1.22		2.05	0.04 *	0.09	4.89					
LO	0.38	0.08	0.26	4.49	0.00 *	0.21	0.55	0.35	0.29	0.25	0.94	1.07
Feedback	0.00	0.00	0.28	4.70	0.00 *	0.00	0.01	0.41	0.30	0.26	0.89	1.12
LMSA	0.00	0.00	0.23	4.06	0.00 *	0.00	0.00	0.31	0.26	0.23	0.96	1.05
MS	−0.53	0.21	−0.14	−2.46	0.01 *	−0.95	−0.10	−0.21	−0.16	−0.14	0.97	1.03

Note. LO = learning outcomes; LMS access = learning management system access; MS = mean satisfaction teaching; SE = standard error; VIF = variance inflation value. * $p < 0.05$.

Table A2. Teaching methodology applied in the intervention groups.

Condition				Variance Proportions			
Dimensions	Eigenvalue	Index	(Constant)	LO	Feedback	LMSA	MS
1	4.72	1.00	0.00	0.00	0.01	0.01	0.00
2	0.15	5.61	0.00	0.00	0.92	0.05	0.00
3	0.12	6.34	0.00	0.01	0.00	0.91	0.01
4	0.01	22.34	0.00	0.66	0.07	0.00	0.34
5	0.003	40.00	0.99	0.33	0.00	0.03	0.65

Note. LO = learning outcomes; LMSA = learning management system access; MS = mean satisfaction teaching.

Table A3. ANOVA between clusters with respect to the variables LO, feedback, LMS access, and MS.

ANOVA						
	Cluster		Error		F	p
	Mean Square	df	Mean Square	df		
LO	3.20	3	0.95	221	3.38	0.02 *
Feedback	159,903.40	3	5924.35	221	26.99	0.000 *
LMS access	6,809,384.83	3	13,042.17	221	522.11	0.000 *
MS	0.3	3	0.14	221	2.71	0.05 *

Note. LO = learning outcomes; LMS access = learning management system access; MS = mean satisfaction teaching; df = degrees of freedom. * $p < 0.05$.

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Chapter 5

Conclusions and Future Lines of Work

Advanced learning technologies such as voice personal assistants have the ability to update the existing education system and provide new learning experiences. In this research, it is examined how voice assistant technology could be used to support students and the impact it could have on their learning processes, as well as the practical use of such technology inside existing virtual learning environments and the efficacy of voice personal assistants in learning environments over time. Research on this topic is limited since voice personal assistants are currently gaining popularity, and there is little literature available on their use when integrated with virtual learning environments and learning management systems to act as a support for university teaching. Likewise, little literature seems to be available on design sciences, regarding the interaction design, perception, and acceptance of voice personal assistants by students.

Voice personal assistants will be at the centre of interest in coming years as they enter into the everyday lives of households. However, the ways they can be used efficiently in the learning process are the subject of research as there are currently many challenges in this regard. One of these challenges is how the integration of voice personal assistants with virtual learning environments and learning management systems requires important technical adjustments, although it is a very promising resource. University teaching has to implement further digitization and move towards what has been called the smart university. This idea is gaining in strength, and situations such as the COVID-19 health crisis have only accentuated this trend. It is a present need, as much as a future one, that must be researched from both a technological and pedagogical perspective, as well as an instructional standpoint.

Looking into the use of voice personal assistants as one of the advanced

learning technologies to be included in learning management systems, the article “Effectiveness of Using Voice Assistants in Learning: A Study at the Time of COVID-19” attempts to verify whether there will be significant differences in access to learning management systems as well as in student learning outcomes depending on use versus non-use of voice personal assistants. Moreover, it also analyzes the students’ perceptions of their usefulness when integrated within learning management systems. According to the findings in this article, students appreciated the possibilities of using voice personal assistants as part of their university environment, but they recognize that this is a new technology in this context and believe that there are aspects that could be improved, both in terms of functionality and interface presentation. Furthermore, students expressed concerns about voice personal assistants invading their personal privacy, which is related to their reluctance to use them.

In the same line of work, and rooted in that motivation to support the research of effectiveness when using voice personal assistants for education, the article “Moodle LMS Integration with Amazon Alexa: A Practical Experience” aims to provide new scientific insight by presenting the work done to establish the basic architecture for an Alexa skill for educational purposes, including its integration with Moodle. Besides, the paper evaluates whether Moodle currently provides the necessary tools for voice-content creation to develop voice-first applications. The outcomes of this article are guidelines for the architecture of an Alexa skill application integrated with Moodle through secure protocols, such as Alexa’s Account Linking Web Service, and confirmation of the need for additional tooling within the Moodle platform for voice-content creation in order to create an appealing voice experience, with the ability to process Moodle data structures and produce sensible sentences that can be understood by users when spoken by Alexa.

On a deeper analysis of the use of advanced learning technologies in learning management systems, with voice assistance as one of such technologies, the article “Using Advanced Learning Technologies with University Students: An Analysis with Machine Learning Techniques” investigates which advanced learning technologies may be best used to predict and classify learning outcomes, learning management system behaviors, and student satisfaction with teachers, and how voice personal assistants take part in such outcomes. The conclusions in this article suggest that using voice assistant technology was not particularly effective, which could be due to the fact that it could only provide students with basic information about their calendar of events. The usage of voice personal assistants capable of providing automatic feedback to learning processes could probably improve these results, noting that implementing this capability within learning management systems is still difficult

and in its early stages of development due to the requirements of advanced artificial intelligence. Nonetheless, the article highlights that advanced learning technologies improve students' performance rates and that their use tends to promote better performance.

Overall, our findings indicate that learning management systems, and Moodle in particular, are not platforms that currently provide the necessary tools for voice-content creation. Our findings indicate that, in order to create a voice experience with the use of Moodle data, there needs to be a middle layer that would process the data and produce sensible sentences that can be comprehended by users when spoken by a voice device. An alternative to building this missing layer of interoperability would be to implement enhancements that would allow Moodle to be ready for voice-content creation. As for future lines of work, our team is considering how such enhancements could be brought to Moodle, either in the form of a Moodle plugin or as an additional application, similar to the Moodle mobile app, but for voice devices. Moreover, creating an additional platform that would bridge the gap between Moodle and voice devices could be an alternative.

Besides voice-content creation, usability can be improved as well, providing a better experience for students when interacting with Moodle via voice instead of traditional visual interfaces. A new line of future work is open for researching how to improve the Moodle platform to be used via voice. A possible path could be to introduce a voice personal assistant within the Moodle mobile app, or perhaps create new plugins for existing web browsers to interact with Moodle via voice directly from the computer. As well, the introduction of additional languages is a subject for future work towards improvement and experimentation. Currently, the skill is only available in Spanish, but English could be very helpful for international students, acknowledging that yet another challenge in voice personal assistants is the lack of language support, since they do not support all languages in the world.

Such a lack of tools for integration of voice personal assistants within learning management systems was also perceived as a reason for the low effectiveness of the Alexa skill developed over the course of this research and used for experimentation. The use of voice personal assistants where automatic feedback actions can be applied to the learning processes would probably improve these results. However, as discussed above, since it involves advanced artificial intelligence technology, implementing such capabilities in learning management systems is difficult and still in its early stages of development. A new avenue for future research opens up to investigate how students feel when asked for feedback directly, determining whether they are willing to reply after the direct instruction or whether they value the option

to opt in or ignore the prompt.

While security and privacy were not the primary research topics in this study, experimentation has proven to be critical in identifying the underlying risks associated with the use of voice personal assistants and finding out how to mitigate them. While most of them have some security and privacy features built in, there are still a number of security and privacy issues to be solved. Manufacturers, researchers, and developers will be better prepared to create and implement robust security control measures if they have a better awareness of security risks.

Several challenges in security and privacy concerns remain open for future research, such as making authentication stronger, improving authorization models and mechanisms, building secure and privacy-aware speech recognition, conducting systematic security and privacy assessments, developing AI-based security and privacy countermeasures, improving user awareness and usability, and studying further profiling attacks and defenses, which appear to be of critical importance [79, 82, 86].

Beyond the technical challenges, we recognize that systematic literature reviews and taxonomy papers concerning voice personal assistants and other related terms currently provide a very focused and specific perception of the domain of study at hand, which complicates the evaluation and comparison of results between domains and fields of research, and produces certain confusion that extends to matters such as concept definitions and lexicon. This line of work is currently being explored, and further exploration is under way, in regards to the cross-disciplinary aspects that potentially influence the engagement displayed between people and voice personal assistants. This research could particularly help future researchers, and therefore, a comprehensive classification of voice personal assistants, combining research findings from several domains, could assist the academic community to further understand and expand the existing research literature.

To summarize, the role of voice personal assistants and their use as components in smart universities is still in the early stages of research, and further study is needed.

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