Minería de datos aplicada al procesamiento automático en el análisis del proceso de enseñanza-aprendizaje

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HACEN CONSTAR: Que la presente tesis doctoral titulada «Minería de datos aplicada al procesamiento automático en el análisis del proceso de enseñanza-aprendizaje», ha sido realizada bajo su dirección por la doctoranda Dña. SANDRA RODRÍGUEZ ARRIBAS, en el Programa de Doctorado «Tecnologías Industriales e Ingeniería Civil» de la Universidad de Burgos, y que cumple con los requisitos necesarios de calidad y originalidad para su defensa.

Y para que conste, se expide la presente certificación en Burgos, a 22 de septiembre de 2021.

Fdo.: José Francisco Díez Pastor   María Consuelo Sáiz Manzanares

A papá y mamá por regalarme una vida de cariño e ilusión en la que me enseñan cada día que el camino de una persona se hace "a poquitos".

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Resumen

Actualmente el proceso de enseñanza-aprendizaje utiliza frecuentemente plataformas interactivas, sistemas de gestión del aprendizaje (LMS - *Learning Management System*) , como herramientas para apoyar y facilitar el aprendizaje de los estudiantes. Estos entornos ofrecen muchas posibilidades de registro de la actividad (*logs*) dentro de la plataforma y de extracción de dicha información. Sin embargo, los LMS no siempre contienen herramientas adecuadas para el análisis de la información, más allá de algunos sencillos procedimientos de *Learning Analytics* (LA) que únicamente posibilitan llevar a cabo análisis de datos sencillos. Por este motivo, para realizar estudios más precisos, lo que se conoce como *Educational Data Mining* (EDM), es necesario aplicar técnicas estadísticas y de minería de datos más sofisticadas y complejas.

El objetivo principal de esta tesis doctoral es el de analizar el proceso de enseñanza-aprendizaje en distintos entornos y etapas educativas, empleando técnicas de minería de datos para la extracción de información y conocimiento.

Esta tesis está dividida en cuatro partes. Un primer capítulo introductorio en el que se explican los conceptos más teóricos así como las técnicas y herramientas aplicadas durante todo el proceso de investigación. Posteriormente, en la segunda parte, se exponen los objetivos de la investigación así como las aportaciones y méritos de esta tesis. En este capítulo encontrarán seis publicaciones a lo largo de las cuales se analizan distintos escenarios y técnicas de enseñanza-aprendizaje en diferentes etapas educativas. Por último, en la parte final del documento se encuentran las conclusiones extraídas tras finalizar todo el proceso de investigación realizado y las líneas futuras en las que seguir trabajando y ampliando el conocimiento.

Palabras clave: *Learning Management Systems*, aprendizaje auto-regulado, minería de datos, tecnología eye-tracking, *Educational Data Mining*.

Abstract

Nowadays the teaching-learning process frequently uses interactive platforms, Learning Management Systems (LMS), as tools to support and facilitate student learning. These environments offer many possibilities for recording activity (*logs*) within the platform and extracting this information. However, LMSs do not always contain appropiate tools for data analysis, beyond some simple Learning Analytics (LA) procedures that only enable simple data analysis to be carried out. For this reason, in order to perform more precise studies, known as Educational Data Mining (EDM), it is necessary to apply more sophisticated and complex statistical and data mining techniques.

The main aim of this doctoral thesis is to analyse the teaching-learning process in different educational environments and stages, using data mining techniques for the extraction of information and knowledge.

This thesis is divided into four parts. The first introductory chapter explains the more theoretical concepts as well as the techniques and tools applied throughout the research process. Subsequently, in the second part, the objectives are shown ant the contributions and merits of this thesis are included too. In this chapter you will find six publications in which different teaching-learning scenarios and techniques are analysed at different educational stages. Finally, in the last part of the document you will find the conclusions drawn at the end of the research process and the future lines in which to continue working and expanding knowledge.

Keywords: Learning Management Systems, self-regulated learning, data mining, eye-tracking technology, Educational Data Mining.

Capítulo 1

Introducción

1.1. Conceptos Teóricos

Esta sección se ha estructurado de forma que aparecen primero los conceptos teóricos relacionados con la docencia online y posteriormente aquellos relativos a las técnicas y algoritmos de mineria de datos que se han aplicado para el análisis de los conjuntos de datos.

1.1.1. eLearning

Son procesos de enseñanza-aprendizaje que se llevan a cabo a través de Internet, caracterizados por una separación física entre el profesorado y el alumnado, donde el alumno/a pasa a ser el centro de la formación, al tener que autogestionar su aprendizaje, con ayuda de tutores y compañeros.

Actualmente el proceso de enseñanza-aprendizaje utiliza a menudo entornos e-learning o de enseñanza online en lugar de hacerlo únicamente de forma presencial (*face-to-face* (F2F)) [33, 79], esta situación se ha intensificado debido a la pandemia mundial por COVID-19 [28, 66]. Sin embargo, la enseñanza *e-learning* presenta una serie de retos por solucionar, como son: el tipo de interacciones que se producen en los espacios virtuales entre profesor/a-estudiante, y entre los y las estudiantes entre si, la personalización del proceso de enseñanza-aprendizaje en función del estilo de aprendizaje de cada alumno/a y del estilo docente, la detección de alumnos/as en riesgo de abandono, y el uso de recursos tecnológicos en los sistemas de gestión del aprendizaje (LMS) realizados desde un buen diseño pedagógico [45, 67, 70].

Por otro lado este tipo de enseñanza tiene varias ventajas sobre la enseñanza tradicional:

- Desaparición de las barreras espacio-temporales: Los estudiantes pueden realizar un curso en cualquier lugar siempre que haya disponible una conexión a Internet, estando accesibles la mayoría de los contenidos cualquier día a cualquier hora. Pudiendo de esta forma optimizar al máximo el tiempo dedicado a la formación.

- Formación flexible: La diversidad de métodos y recursos empleados en este tipo de formación (OPBL, laboratorios virtuales, experiencias *Flipped Classroom*, etc.), facilita al profesorado que pueda adaptarse a algunas de las características y necesidades de los estudiantes. Aunque será necesario que el profesorado tenga competencias digitales para implementar este tipo de recursos dentro de los LMS y así poder sacar el máximo partido posible a la utilización de dichos recursos [65].

- Contenidos actualizados: las novedades y recursos relacionados con el tema de estudio se pueden introducir de manera bastante rápida en los contenidos, de forma que las enseñanzas estén totalmente actualizadas.

- El alumno/a es el centro del proceso de enseñanza-aprendizaje y participa activamente en la construcción del conocimiento, ya que tiene capacidad para decidir el itinerario formativo más acorde con sus intereses aunque siempre bajo la guía del profesor/a.

1.1.2. Online Project-based Learning (OPBL)

El Aprendizaje Basado en Proyectos (ABP) o *Project-Based Learning* (PBL), es una metodología de enseñanza activa que se enfoca en aprender haciendo [84]. Debido a la pandemia mundial por Covid-19, toda la enseñanza pasó a ser online y muchos profesores/as adoptaron esta metodología integrándola en la enseñanza en línea por lo que la conocemos como *Online Project-based Learning* (OPBL).

Muchas investigaciones demuestran que el aprendizaje basado en proyectos puede ayudar a los alumnos/as a desarrollar habilidades especialmente demandadas en el siglo XXI como la colaboración, la comunicación, el pensamiento crítico y la creatividad. También da a los estudiantes la posibilidad de intervenir en su aprendizaje y se presta a una evaluación más auténtica de sus habilidades y capacidades. Además, el PBL permite a los estudiantes aprender y reflexionar sobre problemas del mundo real a través de proyectos bien diseñados y de la autoevaluación.

El uso de la metodología PBL en el aprendizaje a distancia permite a los profesores/as organizar la información relevante para facilitar al estudiante su aprendizaje, al tiempo que ofrece a los estudiantes la oportunidad de colaborar y conectarse entre sí, incluso si no están cara a cara.

Sin embargo, trasladar el PBL a un entorno de aprendizaje *online* o híbrido requiere una planificación cuidadosa e intencionada [58]. Para utilizar con éxito el OPBL deben tomarse en cuenta ciertas consideraciones a la hora de diseñar los proyectos y actividades que deberán realizar los alumnos/as.

1. Hacer que las actividades estén disponibles para todos los dispositivos para que todos los estudiantes puedan participar sin problemas independientemente del dispositivo que empleen para su conexión.

2. Utilizar plataformas de videoconferencia con funciones de colaboración incorporadas para una colaboración significativa, es decir que permitan a los estudiantes implicarse en el aprendizaje y el trabajo en grupo, ya que el trabajo en equipo y la colaboración son esenciales para el OPBL. Los estudiantes se reúnen en pequeños grupos y trabajan juntos para resolver problemas específicos, lo que implica hacerse preguntas, pensar en estrategias y encontrar recursos.

3. Hacer que el trabajo en grupo sea eficaz con herramientas de gestión de proyectos. Estas herramientas permiten a los profesores/as gestionar los grupos de estudiantes y controlar en qué están trabajando, así como mejorar la comunicación con ellos. Además, los estudiantes pueden tener todos los recursos de sus proyectos en un solo lugar.

4. Proporcionar retroalimentación continua y promover la reflexión realizando evaluaciones formativas y sumativas durante el OPBL.

1.1.3. Gamificación

La gamificación es una técnica de aprendizaje que traslada la mecánica de los juegos al ámbito educativo y profesional con el fin de conseguir mejores resultados: obteniendo conocimientos, mejorando habilidades de los estudiantes o trabajadores o recompensando acciones concretas [25]. Este término cuenta con una gran popularidad en los últimos años, sobre todo en entornos digitales y educativos [15].

Es muy importante que los alumnos/as tengan asimiladas las dinámicas de juego que se llevarán a cabo, ya que todas ellas tienen por objeto implicar al alumno/a a jugar y seguir adelante en la consecución de sus objetivos mientras se realiza la actividad. En función de la dinámica que se persiga, el profesor/a deberá explotar más unas u otras y tenerlo en cuenta a la hora de diseñar y desarrollar la actividad.

Las actividades realizadas en el contexto de la gamificación buscan lograr principalmente tres objetivos:

1. Fidelizar al alumno/a con el contenido que se está trabajando.
2. Ser una herramienta motivadora y divertiva dentro de la formación [80].
3. Optimizar y recompensar al alumno/a en algunas tareas dentro de su proceso de enseñanza-aprendizaje.

Hay muchas formas de aplicar la gaminificación dentro del aula, una de las más conocidas y empleadas son los *serious games*

1.1.3.1. Serious Games

El concepto de *serious games* fue explicado por primera vez por Abt Clark en el año 1970 [20]. Son juegos diseñados con un propósito formativo más que para fines de entretenimiento, por lo que son perfectos para incluirse en el proceso de enseñanza-aprendizaje.

Son juegos que incluyen actividades de reflexión sobre una tarea. Una de las razones de su eficacia es que facilitan el desarrollo de estrategias metacognitivas de orientación y planificación durante la resolución de las tareas. Estas tareas cuentan con un diseño estructurado basado en un orden secuencial de las actividades en función de la dificultad como indican varios estudios [21, 50].

Los *serious games* han adquirido gran popularidad en los últimos años y han sido adoptados tanto por instituciones educativas como por empresas, especialmente para programas de formación, investigación e innovación educativa ya que son especialmente eficaces para el aprendizaje de habilidades concretas y el desarrollo de competencias.

A pesar de que hay un gran prejuicio sobre el uso de videojuegos, las estrategias lúdicas propias de los *serious games*, del Aprendizaje Basado en Juegos o la gamificación, permiten a los profesores/as "enganchar" a sus alumnos/as con los contenidos educativos [22] y de esta manera los alumnos/as aprenden al mismo tiempo que se divierten.

1.1.4. Aprendizaje Auto-regulado

Para aprender algo de manera eficaz y significativa debemos aprender a regular los procesos cognitivos y emocionales que intervienen en el proceso de aprendizaje. El ser humano tiene la capacidad de aprender constantemente, pero no todas las formas de aprendizaje son iguales [48].

Hablamos de *Self-Regulated Learning* (SRL) o Aprendizaje Auto-regulado cuando el estudiante es capaz de gestionar los procesos cognitivos y emocionales que están involucrados en el aprendizaje, de forma deliberada. Es decir, el estudiante es capaz de seleccionar aquellas estrategias que le resultan beneficiosas en el momento de aprender, regulando sus emociones y desempeño para alcanzar sus metas. Zimmerman indica que la autorregulación no es una habilidad mental o sinónimo de rendimiento académico, sino que es un proceso de autodirección mediante el cual el estudiante transforma sus habilidades mentales, sean cuales sean, en habilidades académicas [87]. El aprendizaje autorregulado no implica únicamente el dominio de una habilidad mental, sino que también está relacionada con poseer una gran autoconciencia y automotivación.

La autorregulación implica el uso selectivo de procesos específicos que deben adaptarse personalmente a cada tarea del aprendizaje [47], no todos aprendemos lo mismo de la misma forma [16, 17, 74, 78]. Existen numerosas estrategias de aprendizaje, Zimmerman y Martínez Pons [88] detectaron catorce estrategias diferentes empleadas por los alumnos/as: autoevaluación, organización y transformación de la información, planificación y establecimiento de metas y submetas, búsqueda de la información, recogida de datos, autodirección, estructuración del ambiente, autoasignación de sanciones positivas y negativas, repaso y memorización, búsqueda de asistencia académica y revisión o repaso de notas y libros.

Cuando hablamos de que un estudiante realiza un aprendizaje autorregulado hablamos de que está regulando su propia conducta, enfocándola en la adquisición de un contenido, habilidad o tarea académica. El aprendizaje auto-regulado es un proceso cíclico compuesto de tres fases: una fase previa de análisis de la tarea, después una fase de realización de la propia tarea de aprendizaje y, por último, una fase de reflexión. En la figura 1.1 puede observarse un esquema con las tareas que incluye cada fase.

En este tipo de aprendizaje los estudiantes se implican de forma activa en el proceso de adquisición de nuevos conocimientos, haciendo así que ese conocimiento sea más personalizado y, además, más profundo.

1.1.5. Sistemas de gestión del aprendizaje

Los sistemas de gestión del aprendizaje o en inglés *Learning Management Systems* (LMS) son un tipo de software instalado en un servidor web empleado para administrar, controlar y planificar el proceso de enseñanza-

Figura 1.1: Fases del aprendizaje auto-regulado. Fuente: elaboración propia.

aprendizaje. Se componen de dos elementos básicos: un servidor que lleva a cabo las funcionalidades base del sistema y una interfaz de usuario con la que interaccionan los profesores/as, estudiantes y administradores del sistema.

Podemos imaginar los sistemas de gestión del aprendizaje como grandes repositorios de información que permiten a los usuarios tanto almacenar como rastrear el uso de la información desde un único lugar. Cualquier usuario que disponga de un nombre de usuario y contraseña puede acceder al sistema y sus recursos en línea.

Inicialmente se empleaban casi exclusivamente en entornos *e-Learning* pero en la actualidad su uso está ampliamente extendido en todos los entornos de enseñanza-aprendizaje (presencial, en línea o semi-presencial), especialmente en la Educación Superior [12].

Un LMS dota al docente de la capacidad de crear y compartir contenido, monitorizar la participación de los estudiantes y evaluar su rendimiento. En el caso de los estudiantes, el sistema les permite acceder a multitud de recursos y actividades que les ayudarán y facilitarán su aprendizaje como son foros, vídeos, cuestionarios...

1.1.5.1. Características de un LMS

Las características básicas de un *Learning Management System* son:

- **Interactividad**: En este tipo de plataformas el proceso de enseñanza-aprendizaje implica interacciones frecuentes de los usuarios. El dinamismo es clave para tener éxito en la consecución de los objetivos del proceso de enseñanza.

- **Escalabilidad**: El número de usuarios en los distintos roles del sistema no es limitado y puede incrementarse o disminuirse siempre que sea necesario sin perder la calidad de los contenidos y de la enseñanza, lo que sí puede verse afectado en clases exclusivamente presenciales.

- **Accesibilidad**: La plataforma puede ser utilizada incluso por usuarios con ciertas discapacidades ya que tiene opciones de configuración que la hacen asequible a estas personas.
- **Funcionalidad**: La plataforma puede adecuarse a las necesidades y requerimientos de los usuarios y sus exigencias.
- **Flexibilidad**: Los LMS pueden adaptarse a cualquier tipo de cursos.
- **Ubicuidad**: Los usuarios de la plataforma pueden encontrar todo lo que necesiten para la realización y seguimiento de las actividades durante su aprendizaje. Los cursos en la plataforma LMS pueden accederse desde cualquier dispositivo con acceso a Internet sin importar el lugar o el tipo de dispositivo.
- **Posibilidad de integración**: Las plataformas generalmente pueden integrarse en otras herramientas y aplicaciones para proporcionar aprendizajes significativos y más completos.

Este tipo de herramientas facilitan, sin duda, el acceso a la información y recursos ya que permiten aprender en cualquier lugar y momento. Además no exigen profundos conocimientos de informática ni lenguajes de programación para poder utilizarlos, ya que la mayoría son plataformas bastante intuitivas y que cuentan con amplia bibliografía y recursos de apoyo para los usuarios.

Otra de sus grandes ventajas es que, como ya indicamos antes, nos permiten monitorizar la actividad de los usuarios y analizarla como veremos en el siguiente punto [18].

1.1.6. Educational Data Mining o Learning Analytics

El *e-Learning* implica el uso de plataformas LMS donde se generan y almacenan una gran cantidad de datos como ya hemos visto. Si empleamos técnicas de minería de datos para extraer información y conocimiento útil de esa gran cantidad de datos en bruto estamos hablando de *Educational Data Mining* (EDM) [6].

Learning Analytics (LA) se puede definir como la medición, la recopilación, el análisis y la comunicación de datos sobre los alumnos/as y sus contextos, con el fin de comprender y optimizar el aprendizaje y los entornos en los que se produce [43].

Ambos campos de investigación se solapan entre sí e incluso se utilizan indistintamente ya que tienen el mismo objetivo: mejorar la calidad de la educación analizando enormes cantidades de datos para extraer información útil para los interesados.

Utilizar la EDM y el LA para mejorar los procesos de enseñanza y aprendizaje resulta fundamental ya que es útil en muchas áreas diferentes, como la identificación de estudiantes en riesgo, la identificación de necesidades de aprendizaje para diferentes grupos de estudiantes, el aumento de las tasas de abandono o de éxito en la Educación Superior, la evaluación eficaz del rendimiento tanto del estudiante como del propio profesorado e incluso la institución, la maximización de los recursos de las plataformas utilizadas en la enseñanza y la optimización del plan de estudios de las asignaturas [11,27].

El proceso de EDM consta de cuatro fases principales que se enumeran a continuación:

1. **Definición del problema**: es la primera fase en la que se traduce un problema específico en un problema de minería de datos en el que se plantean los objetivos del análisis y las preguntas de investigación.

2. **Preparación y recopilación de datos**: es la fase más extensa del proceso ya que la calidad de los datos es uno de los retos más importantes en la minería de datos. Los datos brutos deben ser identificados, limpiados y almacenados en un formato preestablecido.

3. **Modelado y evaluación**: en este paso se seleccionan y aplican diferentes técnicas de modelado de datos y después se establecen los parámetros y valores óptimos de dichas técnicas.

4. **Despliegue**: es la última fase en la que se organizan y presentan los resultados de la minería de datos mediante gráficos e informes.

Es importante señalar que todo proceso de minería de datos es un proceso iterativo, lo que significa que el proceso no se detiene cuando se despliega una solución concreta. Puede ser sólo una nueva entrada para un nuevo proceso de minería de datos.

La popularidad de estos campos de investigación ha ido creciendo desde principios de la década de 2010, aunque la investigación en EDM comenzó unos años antes y se espera que estos campos sigan expandiéndose debido a los beneficios potenciales y a la relevancia de la investigación actual basada en *Big Data*. [43].

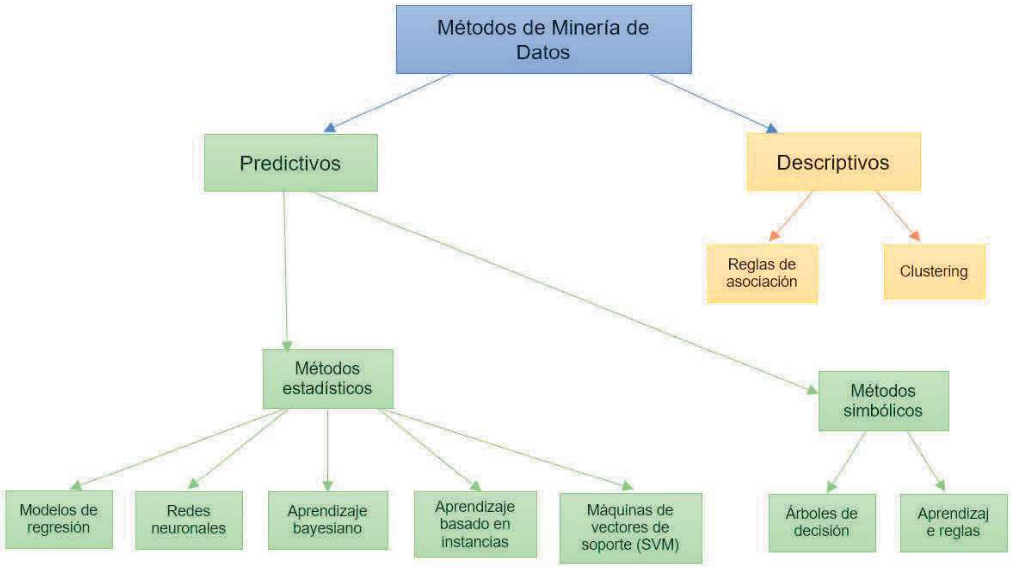


Figura 1.2: Métodos de Minería de datos. Fuente: elaboración propia basada en García el al. [56].

1.1.7. Algoritmos de Minería de Datos

Vivimos en la sociedad de la información y la comunicación, la tecnología que empleamos en el siglo XXI lleva asociada la recopilación y almacenamiento de grandes cantidades de datos. El *data mining* permite encontrar información escondida en los datos que no siempre resulta aparente, ya que, dado el gigantesco volumen de datos existentes, gran parte de ese volumen nunca será analizado.

Podemos definir la minería de datos como un proceso de identificación de información relevante extraída de grandes volúmenes de datos, con el objetivo de descubrir patrones y tendencias, estructurando la información obtenida de un modo comprensible para su posterior utilización [5, 56].

En la figura 1.2 puede verse una taxonomía de los algoritmos de minería de datos.

En la minería de datos hay dos enfoques básicos: el aprendizaje supervisado y el aprendizaje no supervisado. La principal diferencia es que en el aprendizaje supervisado existe un atributo especial o clase, que se utiliza para obtener una función que permite asociar nuevos ejemplos con la clase o predicción asociada. En el aprendizaje no supervisado no existe ninguna clase, en este caso los algoritmos tratan de descubrir patrones ocultos en los datos sin intervención humana en forma de etiquetas asociadas a los datos.

El **aprendizaje supervisado** [7] utiliza conjuntos de datos etiquetados.

Estos conjuntos de datos están diseñados para entrenar o "supervisar" a los algoritmos para que clasifiquen datos o predigan resultados con precisión. Utilizando entradas y salidas etiquetadas, el modelo puede medir su precisión y aprender con el tiempo. Este aprendizaje suele emplearse en problemas de minería de datos de clasificación y regresión.

El **aprendizaje no supervisado** [7] utiliza algoritmos de aprendizaje automático para analizar y agrupar conjuntos de datos sin etiquetar. Estos algoritmos descubren patrones ocultos en los datos sin necesidad de intervención humana, por eso se llama "no supervisado". Estos modelos de aprendizaje se emplean habitualmente para tres tareas principales: agrupación, asociación y reducción de la dimensionalidad.

Por otro lado está el **aprendizaje semisupervisado** [86] que emplea tanto datos etiquetados como no etiquetados en el entrenamiento de los modelos de aprendizaje. Es muy útil cuando es difícil extraer características relevantes de los datos, y cuando se tiene un gran volumen de datos. Como afirman Berthelot et. al [8] "ha demostrado ser un poderoso paradigma para aprovechar los datos no etiquetados y así evitar la dependencia de grandes conjuntos de datos etiquetados".

Pasamos ahora a explicar los algoritmos de minería de datos empleados en los artículos que integran este documento.

1.1.7.1. Algoritmos no supervisados de *clustering*

El *clustering* o agrupación es una técnica de minería de datos que permite agrupar datos en función de sus similitudes o diferencias. Es una técnica que se emplea generalmente con datos no etiquetados como los que se obtienen de los *logs* en los LMS que son los estudiados en esta tesis doctoral.

- ***k*-means**

  k-means [40] es un algoritmo de clasificación no supervisada (clusterización) que agrupa objetos en k grupos basándose en sus características. El agrupamiento se realiza minimizando la suma de distancias entre cada objeto y el centroide de su grupo o cluster. Se conoce como centroide el punto medio de los objetos pertenecientes al grupo. Como medida de similaridad se suele usar la distancia cuadrática o euclídea.

  El algoritmo k-means resuelve un problema de optimización, siendo la función a optimizar (minimizar) la suma de las distancias cuadráticas de cada objeto al centroide de su cluster.

  Los objetos se representan con vectores de números reales de d dimensiones $(x_1,x_2,...,x_d)$ y el algoritmo k-means construye k grupos donde se minimiza la suma de los cuadrados de las distancias de los objetos, dentro de cada grupo $S = \{S_1, S_2, \ldots, S_k\}$, a su centroide. El problema se puede formular de la siguiente manera:

$$\underset{S}{min} E(\mu_i) = \underset{S}{min} \sum_{i=1}^{k} \sum_{x_j \in S_i} \|x_j \mu_i\|^2$$

Donde S es el conjunto de grupos de observaciones cuyos elementos son los objetos x_j representados por vectores, donde cada uno de sus elementos representa una característica o atributo. Tendremos k grupos o clusters con su correspondiente centroide μ_i.

El algoritmo k-means es un método relativamente eficiente. Sin embargo, tenemos que especificar el número de clústeres, por adelantado y los resultados finales son sensibles a la inicialización y, a menudo termina en un óptimo local. Desafortunadamente no hay un método teórico global para encontrar el número óptimo de grupos. Sin embargo, el método *elbow* es ampliamente utilizado como una heuristica para estimar el número adecuado de centros [10].

En general, un k grande probablemente disminuye el error pero aumenta el riesgo de *overfitting*, por lo que este algoritmo puede encontrar agrupamientos poco adecuados. Otra limitacion de k-means, a parte de la necesidad de indicar el numero de *clusters*, es que asigna cada instancia a un agrupamiento, no habiendo la posibilidad de que una instancia no pertenezca a ningún *cluster* o sea ruido.

- ***k-means++***
  En minería de datos, k-means++ es un algoritmo que se utiliza para la selección de los valores iniciales (o "semillas") en el algoritmo k-means mencionado anteriormente. Fue propuesto como una forma de evitar los agrupamientos pobres a veces encontrados por el algoritmo k-means estándar, ya que la aproximación encontrada puede ser arbitrariamente mala con respecto a la función objetivo y al agrupamiento óptimo.

  El algoritmo k-means++ aborda esta deficiencia mediante la especificación de un procedimiento para inicializar los centros de los conjuntos antes de proceder con las iteraciones de optimización del k-means estándar, mejorando la solución óptima de k-means.

  El primer punto se elige de manera aleatoria y entonces el problema para cualquier punto del clúster se puede formular de la siguiente forma:

$$D^2(\mu_0) \leq 2D^2(\mu_i) + 2\|\mu_i - \mu_0\|^2$$

Siendo μ_0 el punto inicial seleccionado y D la distancia entre el punto (μ_i) y el centro más cercano del clúster.

Sin embargo, podemos emplear un proceso en el que elegir esos puntos iniciales de forma más eficiente. Inicialmente también partimos de un punto elegido al azar para ser el centro del clúster. Después de forma iterativa se calcula, para cada observación, la distancia mínima de esa instancia al centro del agrupamiento. Posteriormente se elige el siguiente centro del clúster entre los puntos, teniendo en cuenta que la probabilidad de convertir una observación en centro del clúster es proporcional a $D^2(\mu_i)$. Se repite el proceso hasta que se han elegido el número correcto de agrupamientos.

Una vez realizado este proceso para inicializar los agrupamientos el algoritmo continua con los pasos del k-means *standard* explicado anteriormente.

- ***Fuzzy k-means***

  El algoritmo *fuzzy* k-means para el análisis de clústeres, fue presentado por Bezdek y Dunn [9], el cual combina los métodos basados en la optimización de la función objetivo con los de la lógica *fuzzy*, término presentado por Lofty Zadeh [85].

  Este algoritmo surge de la necesidad de mejorar los clusters producidos por el procedimiento k-means que se denominan clusters "duros" o "nítidos", ya que cualquier vector de características x es o no es miembro de un clúster concreto. Esto contrasta con los clústers "blandos" o "difusos" (*fuzzy*), en los que un vector de características x puede tener un grado de pertenencia distinto a cada clúster.

  El algoritmo *fuzzy* k-means realiza la formación de agrupamientos a través de una partición suave de los datos, es decir, un dato no tendría pertenecía exclusiva a un solo grupo, sino que podría tener diferentes grados de pertenencia a distintos grupos. Este algoritmo, utiliza k particiones difusas de esos vectores de características, para encontrar la mejor agrupación de los puntos.

  Este procedimiento calcula las medias $(m_1, m_2, \ldots, m_k)$ iniciales de cada clúster para encontrar el grado de pertenencia de un dato en un clúster, partiendo de un número aleatorio de clústers k que generalmente se inicializa como en el algoritmo k-means. Mientras que no se produzcan cambios en esas medias se calcula el grado de pertenencia de cada dato x_j en el clúster i:

$$u(j,i) = \frac{e^{-(\|x_j - m_i\|^2)}}{\sum_j e^{-(\|x_j - m_i\|^2)}}$$

Siendo m_i la media *fuzzy* de todos los datos del cluster i:

$$m_i = \frac{\sum_j^i u(j,i)^2 x_j}{\sum_j u(j,i)^2}$$

Tiene la ventaja de que maneja de forma más natural las situaciones en las que las subclases se forman mezclando o interpolando resultados, de forma que tiene más sentido decir que un dato está en un 40 % en el clúster 1 y en un 60 % en el clúster 2, en lugar de tener que asignar ese dato completamente a un clúster o a otro.

Este tipo de algoritmo se aplica ampliamente en la ingeniería agrícola, la astronomía, la química, la geología, el análisis de imágenes, el diagnóstico médico, el análisis de formas y el reconocimiento de objetivos. Además, es un algoritmo adecuado para tratar los problemas relacionados con la capacidad de comprensión de los patrones, los datos incompletos o con ruidos, la información de medios mixtos, la interacción humana y puede proporcionar soluciones aproximadas más rápidamente que otros algoritmos [34].

- ***DBSCAN***

  Density-Based Spatial Clustering of Applications with Noise (DBSCAN) fue presentado en 1996 por Ester et al. [24] como una forma de identificar agrupamientos siguiendo el modo intuitivo en el que lo hace el cerebro humano, identificando regiones con alta densidad de observaciones separadas y regiones de baja densidad.

  DBSCAN evita el problema que tienen otros algoritmos de clusterización siguiendo la idea de que, para que una observación forme parte de un cluster, tiene que haber un mínimo de observaciones vecinas dentro de un radio de proximidad y de que los clusters están separados por regiones vacías o con pocas observaciones [24,36], ya que en otros algoritmos todas las instancias, incluso las anómalas o consideradas ruido siempre pertenecen a un clúster.

El algoritmo DBSCAN utiliza dos parámetros:

1. Épsilon ε: radio que define la región vecina a una observación (dato), también llamada ε-*neighborhood*.
2. *Minimum points* ($minPts$): número mínimo de observaciones dentro de la región épsilon, dentro del clúster.

Empleando estos dos parámetros, cada observación del conjunto de datos se puede clasificar en una de las siguientes tres categorías que, además pueden observarse en la figura 1.3:

1. *Core point* (centro) (p): observación que tiene en su ε-*neighborhood* ($Nbhd$) un número de observaciones vecinas igual o mayor a $minPts$.
$$|Nbhd(p, \varepsilon)| \geq minPts$$
2. *Border point* (borde) (q): la observación no satisface el mínimo de observaciones vecinas para ser *core point* pero que pertenece al ε -*neighborhood* de otra observación que sí es *core point*.
$$|Nbhd(q, \varepsilon)| \leq minPts$$
3. *Noise* u *outlier*: observación que no es centro ni borde.

Por último, empleando las tres categorías anteriores se pueden definir tres niveles de conectividad entre observaciones:

1. Directamente alcanzable (*direct density reachable*): una observación A es directamente alcanzable desde otra observación B si A forma parte del ε-*neighborhood* de B y B es un *core point*. Por definición, las observaciones solo pueden ser directamente alcanzables desde un *core point*.
2. Alcanzable (*density reachable*): una observación A es alcanzable desde otra observación B si existe una secuencia de *core points* que van desde B a A.
3. Densamente conectadas (*density conected*): dos observaciones A y B están densamente conectadas si existe una observación *core point* C tal que A y B son alcanzables desde C.

Estos últimos casos pueden observarse de forma más gráfica en la figura 1.4.

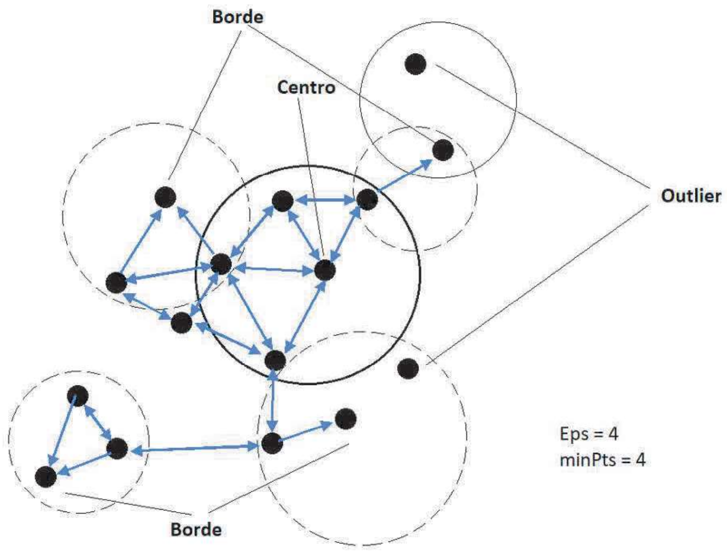


Figura 1.3: Tipos de puntos del algortimo DBSCAN. Fuente: Elaboración propia basada en Hasler et al. [36]

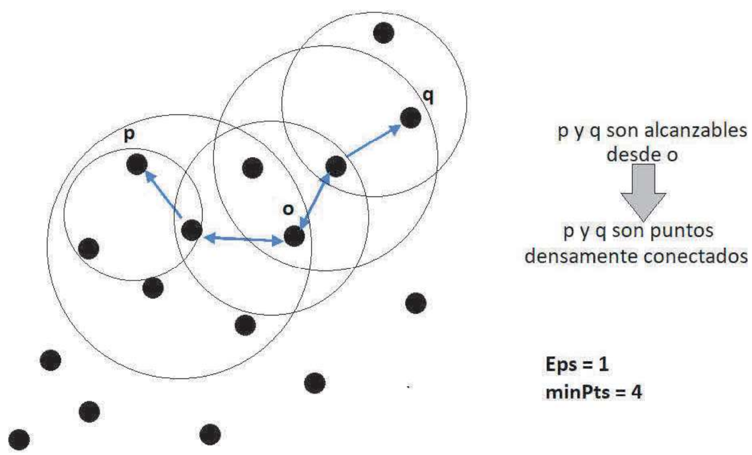


Figura 1.4: Ejemplo tipos de observaciones en DBSCAN. Fuente: Elaboración propia basada en Hasler et al. [36]

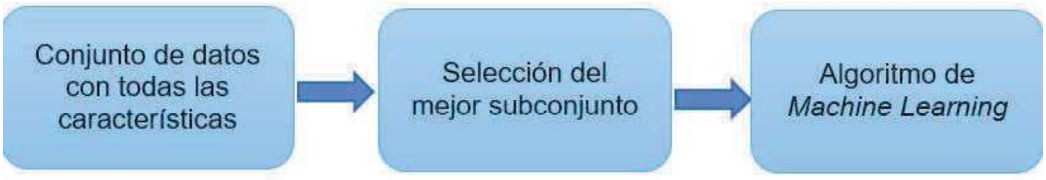


Figura 1.5: Método de Filtrado. Fuente: Elaboración propia

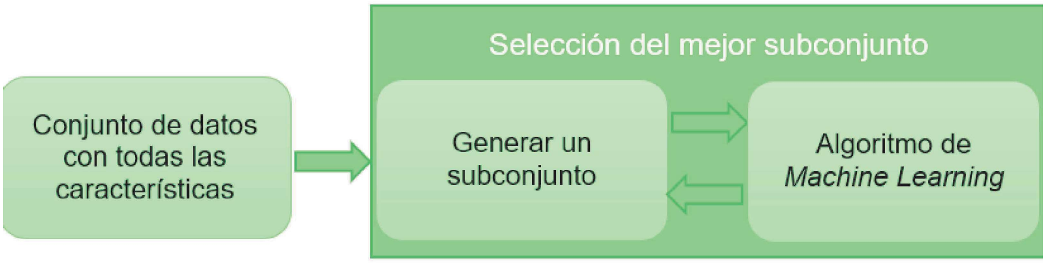


Figura 1.6: Método de Envoltura. Fuente: Elaboración propia

1.1.7.2. Algoritmos supervisados de selección de características

Hay numerosos métodos de selección de características [19], estos nos permiten reducir el tiempo de cálculo, mejorar el rendimiento de las predicciones y comprender mejor los datos en las aplicaciones de aprendizaje automático o reconocimiento de patrones.

Estos métodos se pueden dividir en tres grandes categorías:

1. **Filtrado** (ver figura 1.5): utilizan técnicas de clasificación de variables como criterio principal para la selección de variables con información útil sobre las distintas clases de los datos. Estos métodos se utilizan generalmente como un paso de preprocesamiento de datos ya que la selección de características es independiente de cualquier algoritmo de *Machine Learning*.

2. **Envoltura** (ver figura 1.6): utilizan el predictor como caja negra y el rendimiento del predictor como función objetivo para evaluar el subconjunto de variables. Estos métodos necesitan un algoritmo de *Machine Learning* y utilizan su rendimiento como criterio de evaluación. El problema se reduce esencialmente a un problema de búsqueda.

3. **Integrados**: combina las cualidades de los métodos anteriores. Pretender reducir el tiempo de cálculo que se emplea en reclasificar diferentes subconjuntos, lo que se hace en los métodos envolventes, incorporando

la selección de características como parte del proceso de entrenamiento. Los algoritmos *Ridge* y LASSO (*Least Absolute Shrinkage and Selection Operator)* son ejemplos de esta categoría, ya que que tienen funciones de penalización incorporadas para reducir el sobreajuste.

Pasemos ahora a explicar los algoritmos de selección de características empleados en los análisis de datos realizados en el artículo sobre la tecnología *Eye-Tracking* y el proceso de aprendizaje [69].

- ***Gain Ratio***

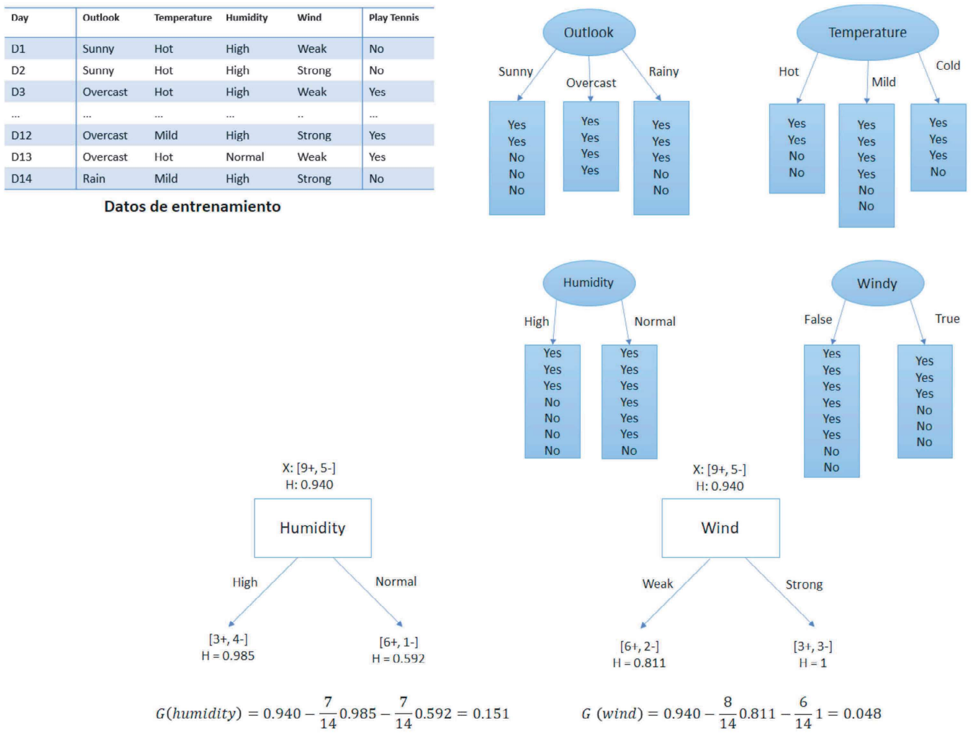
  Este algoritmo es un método de selección de características que pertenece a los métodos de filtrado. Se basa en la entropía para asignar pesos a los atributos discretos en función de su correlación entre el atributo y una variable objetivo. La entropía (H) mide la incertidumbre de cada dato, es decir la cantidad de información que puede aportar cada dato. Hay que tener en cuenta que los datos con menor probabilidad de aparecer aportan una mayor información relevante, por lo tanto su entropía es máxima. Se calcula como:

  $$H(X) = -\sum_{i=1}^{k} p(x_i)logp(x_i)$$

  Donde $X = x_1, x_2, \ldots, x_k$ es el conjunto de datos y $p(x_i)$ la probabilidad de cada observación dentro del conjunto de datos.

  El algoritmo *gain ratio* se centra en la métrica de ganancia de información [38], tradicionalmente utilizada para elegir el atributo en un nodo de un árbol de decisión con el método ID3 introducido por Quinlan [53]. Ésta es la que genera una partición en la que los ejemplos se distribuyen de forma menos aleatoria entre las clases. Este método fue mejorado por Quinlan en 1993 [39], ya que detectó que la ganancia de información se calculaba con un favoritismo injusto hacia los atributos con muchos resultados. Para corregirlo, añadió una corrección de valor basada en la normalización por la entropía de ese atributo.

  Si Y es la variable que se quiere predecir, el coeficiente de ganancia normaliza la ganancia dividiéndola por la entropía de X. Así, el método de construcción de árboles de decisión C4.5 [54] utiliza esta medida. Desde punto de vista de la minería de datos, esta selección de atributos podría entenderse como la selección de atributos como mejores candidatos para la raíz de un árbol de decisión.



Day	Outlook	Temperature	Humidity	Wind	Play Tennis
D1	Sunny	Hot	High	Weak	No
D2	Sunny	Hot	High	Strong	No
D3	Overcast	Hot	High	Weak	Yes
...	...	...	...	..	...
D12	Overcast	Mild	High	Strong	Yes
D13	Overcast	Hot	Normal	Weak	Yes
D14	Rain	Mild	High	Strong	No

Figura 1.7: Ejemplo algoritmo *gain ratio*. Fuente: elaboración propia basada en Witten et al. [83] y Mitchell et al. [49]

Siendo H la entropía, la ecuación del algoritmo es:

$$gain\ ratio = \frac{H(Clase) + H(Atributo) - H(Clase, Atributo)}{H(Atributo)}$$

En la imagen 1.7 se puede ver un sencillo ejemplo que ilustra este algoritmo. Partiendo de una tabla de datos de entrenamiento, y de árboles de decisión que muestran los datos de dicha tabla, se calcula la ganancia G de cada clase. El conjunto de datos viene representado por X y H, como ya sabemos, es la entropía.

- ***Symmetrical uncertainty***
  Este algoritmo es un método de selección de características que, al igual que el algoritmo *gain ratio* pertenece a los métodos de filtrado y también se basa en la entropía [37].

  El algoritmo *symmetrical uncertainty* normaliza los valores en el rango [0, 1] y, también, normaliza la ganancia según la siguiente ecuación, donde H es la entropía:

$$symmetrical\ uncertainty = 2 \times \frac{H(Clase) + H(Atributo) - H(Clase, Atributo)}{H(Atributo) + H(Clase)}$$

- ***chi-cuadrado***
  Chi-cuadrado es un algoritmo de selección de características que pertenece al tipo de filtrado. Este algoritmo trata de obtener los pesos de cada característica mediante la prueba de chi-cuadrado (en caso de que las características no sean nominales, tienen que estar ya discretizadas). El resultado de la selección es el mismo que el coeficiente V de Cramer [23]. La ecuación del algoritmo chi-cuadrado es la siguiente:

  $$\chi^2 = \sum_{i=1}^{k} \frac{(O_i + E_i)^2}{E_i}$$

  Donde O_i es la frecuencia absoluta observada o empírica, E_i es la frecuencia esperada y k es el número máximo de características seleccionadas.

1.2. Técnicas y Herramientas

En esta sección se presentan las herramientas de software y tecnologías empleadas en los artículos. Las herramientas se han empleado tanto para la recopilación de los datos de estudio como para la realización de análisis de los datos.

1.2.1. *Modular Object - Oriented Dynamic Learning Enviroment* (Moodle)

Moodle es una plataforma de aprendizaje diseñada para proporcionar a educadores, administradores y estudiantes un sistema integrado único, robusto y seguro para crear ambientes de aprendizaje personalizados [4]. Esta plataforma proporciona un conjunto de herramientas centradas en el estudiante y ambientes de aprendizaje colaborativo [42], que le dan poder, tanto a la enseñanza como al aprendizaje y que está disponible en más de 120 idiomas. Además, es un programa de código abierto , bajo la Licencia Pública

General GNU (*General Public License*), por lo que cualquier persona puede adaptar, extender o modificar Moodle, tanto para proyectos comerciales como no-comerciales, sin pago de cuotas ni licencias.

Esta plataforma es ampliamente utilizada en distintos centros educativos alrededor del mundo, esto se debe principalmente a sus características [2,18]:

- Sistema escalable en cuanto a la cantidad de alumnos/as y de cursos.
- Creación de cursos virtuales y entornos de aprendizaje virtuales con multitud de actividades y recursos.
- Puede emplearse como complemento de información digital para cursos presenciales.
- Ofrece la posibilidad de utilizar diversos métodos de evaluación y calificación en función de las características del curso y de las actividades.
- Accesibilidad y compatibilidad desde cualquier navegador web, independiente del sistema operativo utilizado.

Moodle dispone de multitud de recursos (archivos, libros, carpetas, vídeos...) que los profesores/as pueden utilizar dentro de sus cursos y numerosas actividades que solicitar a los alumnos/as, que pueden ser evaluadas.

Por otro lado, el uso de este tipo de plataformas de aprendizaje puede no resultar sencillo para algunos usuarios. En uno de los artículos que componen esta tesis se puede ver en profundidad cómo el uso de los recursos y actividades de Moodle es distinto en función del perfil del docente y de los alumnos/as [65]. Además, otro gran inconveniente son los posibles fallos en los servidores o caídas del servicio de internet que dejan al usuario inhabilitado para realizar sus actividades.

1.2.1.1. UBUVirtual

UBUVirtual es la plataforma de e-learning de la Universidad de Burgos, basada en la herramienta de software libre Moodle, que permite proveer de recursos formativos al alumnado y de herramientas metodológicas al profesorado para facilitar el proceso de enseñanza-aprendizaje y de evaluación continua en el Espacio Europeo de Educación Superior, tanto para enseñanza on line como enseñanza presencial [1].

Como se indicó en el anterior punto el entorno Moodle puede ser modificado o adaptado por cualquier persona, en el caso de UBUVirtual la plataforma aparece modificada según las especificaciones de personalización requeridas

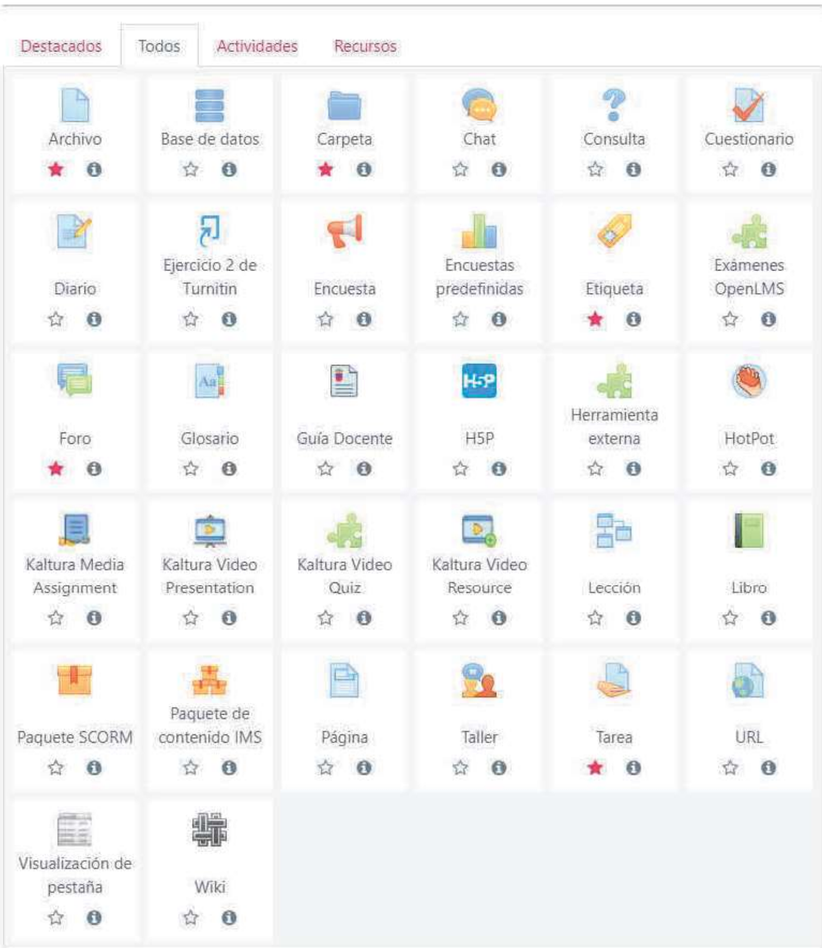


Figura 1.8: Recursos y actividades disponibles en UBUVirtual. Fuente: UBU-Virtual [1]

por la Universidad de Burgos. En la imagen 1.8 pueden verse los recursos y actividades disponibles en la plataforma UBUVirtual en la actualidad.

UBUVirtual, almacena un amplio conjunto de *logs* o registros de las interacciones que los usuarios realizan con la plataforma y los recursos y actividades de los cursos. Esto facilita el almacenamiento de los datos para su posterior análisis empleando técnicas estadísticas y de Minería de Datos como plantea esta tesis doctoral.

Figura 1.9: Logo e-Orientación. Fuente: e-Orientación [63]

Figura 1.10: Panel de agrupaciones en e-Orientación. Fuente: e-Orientación [63]

1.2.1.2. *Plugin* e-Orientación

Este *plugin* ha sido desarrollado dentro del proyecto PR19-0760.1/0 de la Universidad de Burgos. Está diseñado para que se pueda incluir en las plataformas tipo Moodle donde le permitirá al docente crear agrupaciones personalizadas, en función de los componentes y contextos disponibles, dentro de un curso en el que imparta docencia [63, 64].

Los contextos son los recursos y actividades (cuestionarios, enlaces, vídeos, entregas...) que hay en el curso donde se encuentra una agrupación. Las agrupaciones son creadas por los docentes, seleccionando los recursos y actividades que les interesan, y asocian una etiqueta para la identificación de cada uno. En la imagen 1.10 aparece la pantalla en la que el docente puede ver todas las agrupaciones creadas en el curso y crear nuevas empleando el botón de arriba a la derecha.

Por cada agrupación, se podrá visualizar una tabla que muestra el número de veces que cada usuario ha accedido a un contexto de la agrupación. El docente podrá definir un valor de referencia para la desviación típica y se resaltarán todos los valores de la tabla que se desvíen de ese valor (ver imagen 1.11).

Este *plugin* permite la exportación a diferentes formatos de la tabla gene-

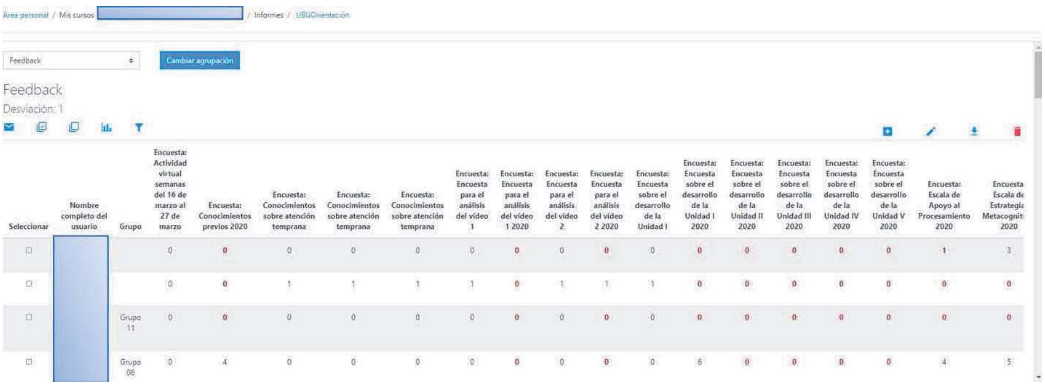


Figura 1.11: Tabla de datos de una agrupación. Fuente: e-Orientación [63]

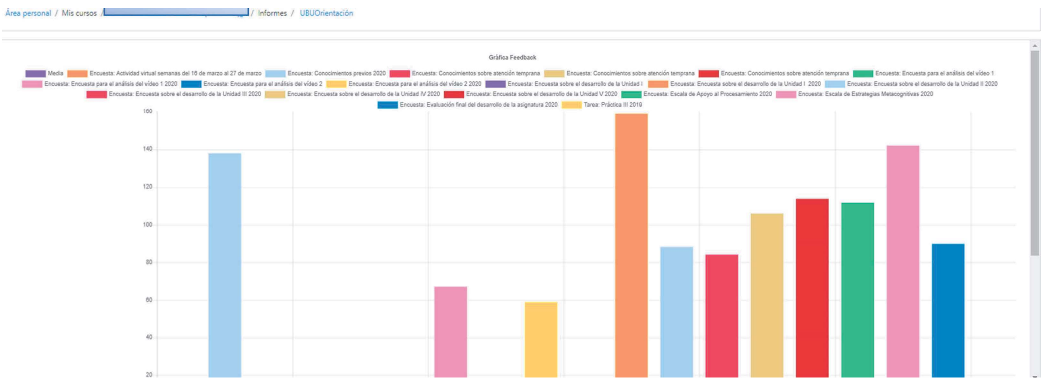


Figura 1.12: Gráfico de barras de e-Orientación. Fuente: e-Orientación [63]

rada con las agrupaciones creadas lo que facilita el posterior análisis de datos porque se exportan los datos ya agrupados basados en el estilo de enseñanza de cada profesor/a, ya que es el propio docente quien crea sus agrupaciones.

Además, incluye varias opciones de visualización de datos en una gráfica de barras donde se observa el número total de accesos a cada componente (véase imagen 1.12). A parte, se representa en forma de gráfico lineal la media de accesos por elemento. La gráfica generada con las mediciones se podrá descargar como imagen para su posterior análisis.

Esta extensión de Moodle es altamente recomendable para aquellos docentes a los que el análisis de los *logs* en bruto, que se pueden descargar de los sistemas LMS, les resulte complicado porque su principal ventaja es la posibilidad de descargar los datos ya agrupados en función de los criterios del docente. Tiene una interfaz sencilla de utilizar y facilita mucho las tareas de limpieza de datos antes de comenzar los análisis de datos más avanzados.

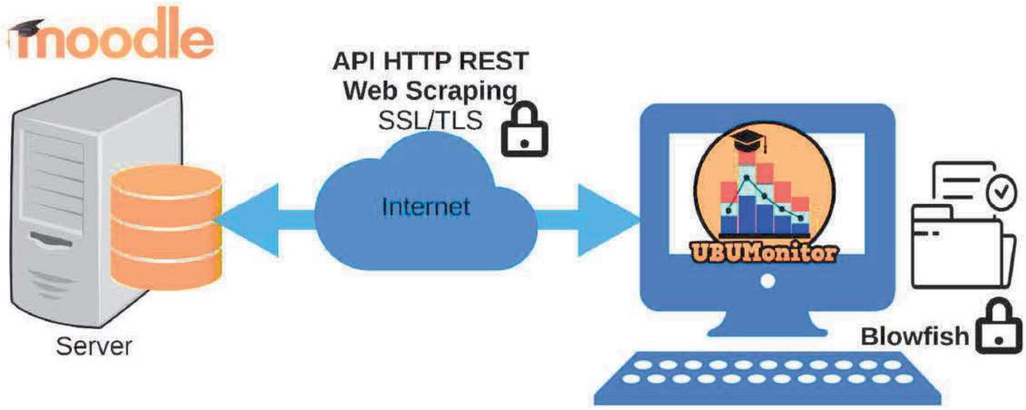


Figura 1.13: Diagrama de funcionamiento de UBUMonitor Fuente: Ji et al. [51].

1.2.2. UBUMonitor

Es una aplicación de escritorio ejecutada en el lado del cliente, implementada con Java, que posee una interfaz gráfica desarrollada en JavaFX [51]. La aplicación se conecta con el servidor Moodle seleccionado, a través de los servicios web y la API REST proporcionados por el propio servidor. En el caso que no se dispongan de servicios web para recuperar algunos datos concretos, la aplicación emplea técnicas de *web scraping*. Toda la comunicación entre el servidor Moodle y el cliente UBUMonitor se realiza de forma segura y encriptada mediante el conjunto de protocolos HTTPS. Como resultado de las consultas realizadas al servidor se obtienen los datos en formato JSON y CSV, procesándose y transformándose en el cliente a objetos Java.

Para la visualización de los datos recolectados se utiliza la solución híbrida de aplicar Java y embeber páginas web con distintas bibliotecas gráficas JavaScript, dentro de la aplicación de escritorio. Los datos se pueden guardar en el cliente para optimizar los tiempos de acceso en las consultas y el acceso a los datos sin conexión, utilizando el mecanismo de serialización disponible en Java. Los ficheros serializados con los datos de las asignaturas se almacenan encriptados con el algoritmo Blowfish [57] que se explicará con más detalle en el siguiente apartado, (ver la imagen 1.13). UBUMonitor es una aplicación de código abierto, con licencia MIT y gratuita e incluye 4 módulos:

- **Visualización**: permite un análisis de las frecuencias de acceso en componentes, eventos, secciones o curso visto en Moodle con opciones de análisis de los registros en distintos tipos de gráficos. Además, todas las opciones de visualización permiten la exportación en formato gráfico y en formato CSV, lo que resulta muy útil para la elaboración de

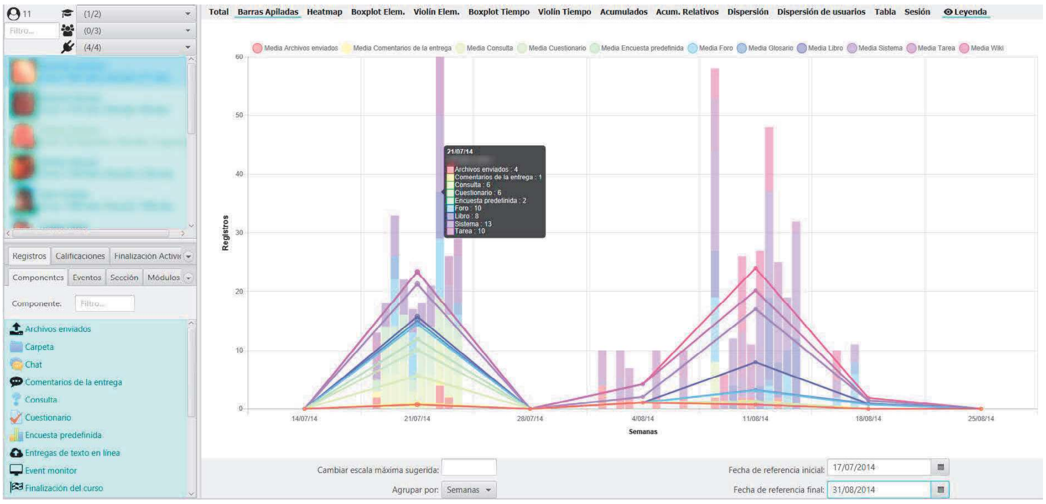


Figura 1.14: Gráfico de barras apiladas de UBUMonitor. Fuente: UBUMonitor [51]

informes o su posterior análisis en otras herramientas. En la figura 1.14 aparece el gráfico de barras apiladas que muestra el número de registros para cada uno de los usuarios seleccionados. Se utilizan diferentes colores para cada uno de los elementos y también se apilan las líneas que indican el valor medio de los usuarios filtrados en ese momento [51].

- **Comparación**: analiza los registros de los estudiantes en los distintos componentes, eventos, secciones o curso visto en Moodle, así como las calificaciones y finalización de actividades, dando información sobre las frecuencias desde una comparativa visual. Este módulo cuenta con varias opciones de visualización distintas, en la figura 1.15 aparece un diagrama de caja con las calificaciones de los alumnos/as donde podemos ver los máximos, mínimos, la mediana, cuartiles primero y tercero, y *ouliers* (son puntos más gruesos).

- **Riesgo de Abandono**: proporciona información por intervalos (de 0-3 días, de 3-7 días, de 7-14 y más de 14 días) sobre los accesos de los estudiantes a la asignatura y a la plataforma Moodle. En estos gráficos se analiza el compromiso de los alumnos/as con la asignatura (ver imagen 1.16) [51].

- ***Clustering***: permite hallar los agrupamientos empleando distintos algoritmos (k-means++, *fuzzy* k-means, DBSCAN, etc) y diferentes distancias (euclidea, manthattan, etc.) que se procesan utilizando librerías de Java. Esta funcionalidad es bastante compleja por lo que su uso está

Figura 1.15: Diagrama de caja de comparativa de grupos en UBUMonitor. Fuente: UBUMonitor [51]

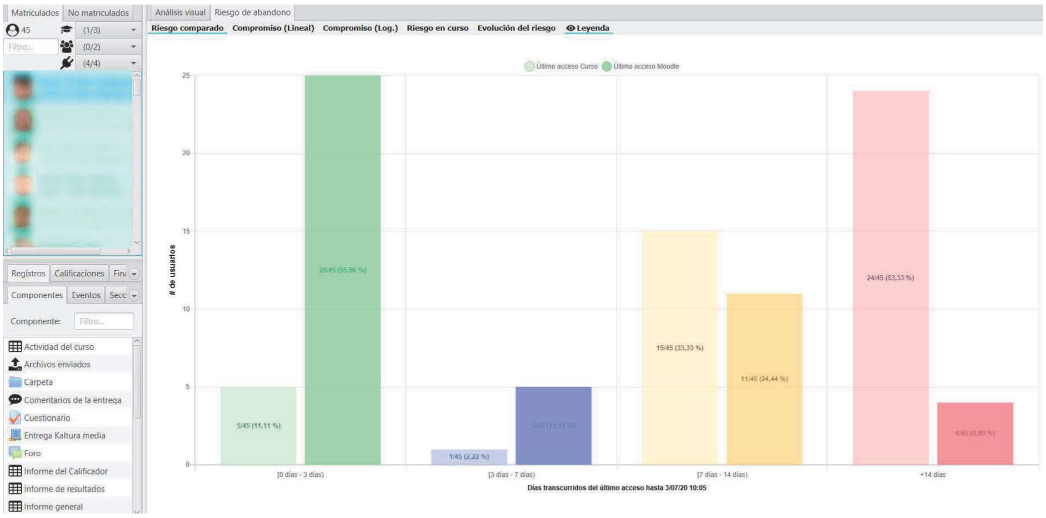


Figura 1.16: Gráfico riesgo de abandono comparado. Fuente: UBUMonitor [51]

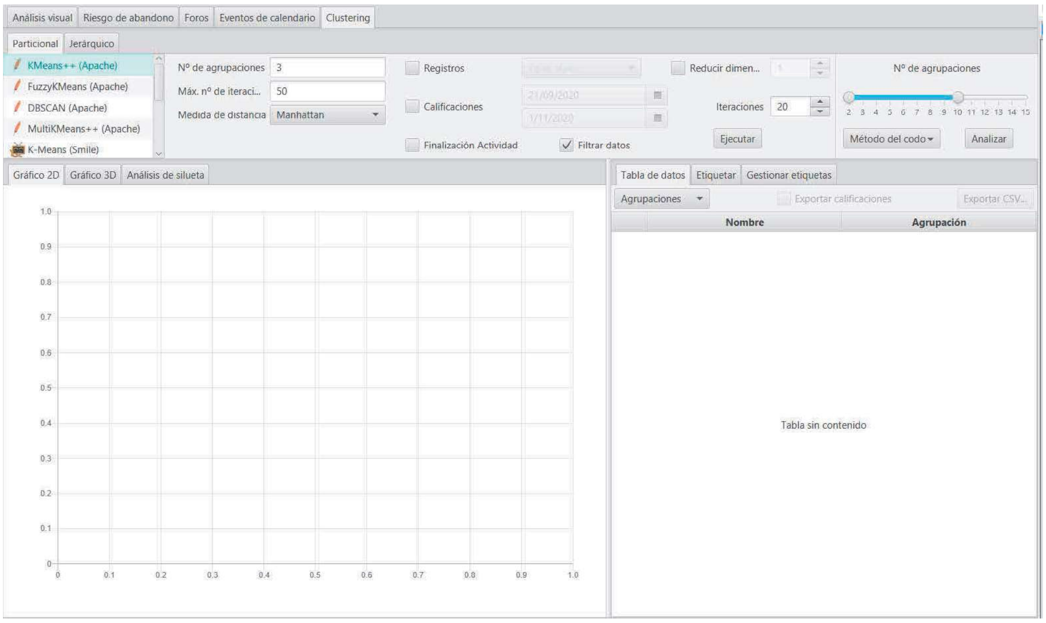


Figura 1.17: Ventana principal de *clustering*. Fuente: UBUMonitor [51]

recomenado para usuarios avanzados con cierta experiencia en el campo [51]. Una vez que se selecciona el algoritmo que se desea aplicar entre las opciones disponibles, hay que ajustar los parámetros necesarios para su funcionamiento los cuales son distintos para cada algoritmo (ver imagen 1.17).

1.2.2.1. Algoritmo Blowfish

Es un algoritmo codificador de uso general, que no tiene patente, creado por Bruce Schneier [57]. Blowfish es un algoritmo de cifrado de clave simétrica, ya que utiliza la misma clave tanto para cifrar como para descrifrar mensajes, que utiliza grupos de bits de longitud fija (bloques) y una longitud variable de clave. Su funcionamiento puede verse en la imagen 1.18, el mensaje de texto plano de 64 bits se divide primero en dos cadenas de 32 bits. Se realiza una operación XOR con los 32 bits de la“izquierda” y el primer elemento de la clave K para crear un valor encriptado, que se ejecuta a través de una función de transformación llamada F. Seguidamente se realiza la misma operación con los 32 bits de la “derecha” del mensaje para producir otro valor encriptado. Después se intercambian posiciones (la cadena de la derecha pasa a ser la de la izquierda y la de la izquierda es ahora la de la derecha) y se repite el proceso anterior 15 veces más con miembros sucesivos

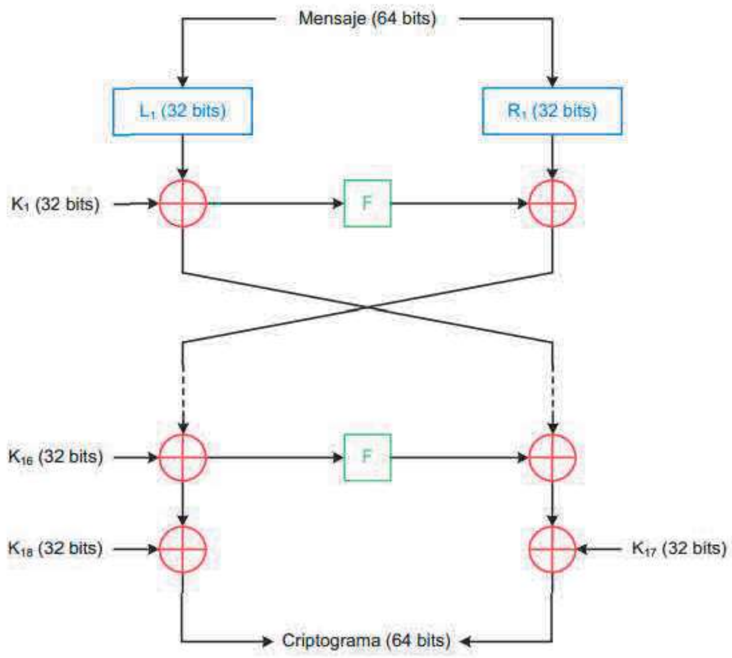


Figura 1.18: Diagrama de funcionamiento del algoritmo Blowfish. Fuente: `http://lumbreras-criptografia.blogspot.com/2013/07/cifrados-por-bloque-blowfish.html`

de la clave. Por último, a los valores resultantes del proceso se les aplica una operación XOR con las dos últimas entradas de la clave (entradas 17 y 18), y se recombinan para producir el texto cifrado final de 64 bits.

1.2.3. Técnicas de visualización

La visualización de los datos es una representación gráfica de la información contenida en esos datos [14]. Empleando elementos visuales se facilita la comprensión de los propios datos [41], ver *outliers*, detectar patrones...

Las principales **ventajas** de emplear este tipo de técnicas son:

- La atención se centra en los colores y patrones, permitiendo distinguir rápidamente distintos tipos de datos y comprender la información y el mensaje más rápido.
- Se identifican las tendencias y valores erróneos muy rápidamente en comparación con los datos en formato texto o en una tabla.

Figura 1.19: Ejemplo de *heatmap*. Fuente: UBUMonitor [51]

- Permiten comprender grandes cantidades de datos con facilidad.

Existen muchas técnicas de visualización de datos distintas: gráficos, tablas, mapas, infografías, *dashboards*, nubes de palabras... Pasamos a explicar en mayor profundidad las más importantes usadas en los artículos.

1.2.3.1. *Heatmaps*

Los *heatmaps* o mapas de calor [35] representan la información utilizando una termografía, es decir, establecen una jerarquía de dos polos. En un extremo, se suelen usar el color rojo en el extremo opuesto suele utilizarse una gama de colores fríos (azul, verde) como puede verse en la imagen 1.19 donde aparece representada la interacción de los alumnos/as con los recursos disponibles en el aula virtual de una asignatura. Los datos están organizados por semanas y el color verde indica mucha interacción de ese alumno/a en esa semana, mientras que el rojo indica ninguna interacción. En la gama de celdas amarillas cuanto mayor es la interacción del alumno/a más intenso y cercano al verde es ese tono amarillo.

Los mapas de calor cumplen con todas las ventajas principales que se han explicado anteriormente en la introducción de la sección por este motivo se optó por emplear este tipo de visualización de datos en los artículos. Permiten observar y comprender una gran cantidad de datos con un simple vistazo gracias a la gama de colores empleados y además facilitan la identificación de tendencias en los datos.

Los datos empleados en todos los artículos de la tesis son datos educativos relacionados con el proceso de enseñanza-aprendizaje en distintas etapas educativas. Gran cantidad de los datos analizados han sido extraídos directamente de sistemas LMS, que ya explicamos con anterioridad, y que indican la interacción de los distintos usuarios con los recursos y actividades disponibles en las aulas virtuales [61, 72]. Representar estos datos en forma de *heatmap* en lugar de con otro tipo de gráfico nos permite ver con facilidad la tendencia de interacción de los usuarios con recursos y actividades que es información muy relevante para los docentes para, entre otras cosas, prevenir el riesgo de abandono. Ya que en este tipo de visualización tanto las interacciones, como la falta de ellas son representadas.

1.2.3.2. Diagrama de Sankey

Un diagrama de Sankey es un tipo de diagrama de flujo que permite representar el conjunto de relaciones de un grupo de valores a otro [46]. Los valores que se conectan se llaman nodos y las conexiones se llaman enlaces. Estos diagramas se utilizan cuando se quiere mostrar una correspondencia de muchos a muchos entre dos dominios o múltiples caminos a través de un conjunto de etapas.

La anchura de las líneas se utiliza para mostrar sus magnitudes, por lo tanto cuanto mayor sea la línea, mayor será la cantidad de flujo. Las líneas de flujo pueden combinarse o dividirse a través de sus trayectorias en cada etapa de un proceso. El color se puede utilizar para dividir el diagrama en diferentes categorías o para mostrar la transición de un estado a otro.

Resultan visualmente muy atractivos y facilitan el seguimiento de la información cuando existe correspondencia múltiple entre los datos. En la imagen 1.20 aparece un ejemplo de este diagrama en el que vemos el análisis de sentimiento de las respuestas dadas por los alumnos y alumnas a dos preguntas de una encuesta de satisfacción realizada. En el lado izquierdo aparecen los posibles sentimientos que muestran las respuestas (positivo, negativo o neutro) y en el lado derecho la pregunta de la encuesta. Como se aprecia en la imagen la mayoría de opiniones dadas sin positivas en ambas preguntas.

1.2.4. Tecnología Eye-Tracking

Esta tecnología realiza la monitorización y seguimiento ocular de una persona, lo que nos permitirá saber comportamientos visuales del usuario cuando interacciona con el sistema y la pantalla.

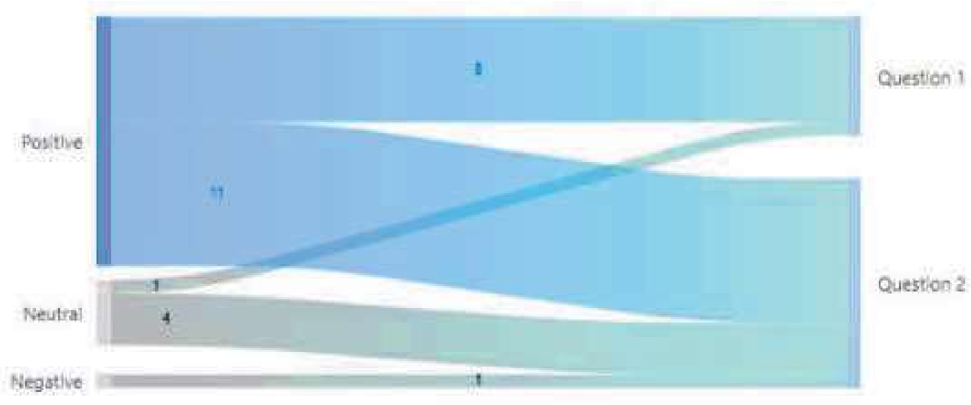


Figura 1.20: Ejemplo de gráfico Sankey. Fuente: Artículo propio publicado [72]

Se utiliza un *eyetracker* como herramienta para realizar las mediciones. Hay varios tipos de *eyetracker* generalmente consisten en un dispositivo especial colocado cerca de la pantalla, que lanza rayos infrarrojos a los ojos del usuario. La dirección que siguen estos rayos va de la pupila del usuario al aparato, permitiendo así calcular con precisión dónde está mirando. En concreto, para la recopilación de datos de análisis en esta tesis se empleó el sistema *iView X*, con el *software SMI Experimenter Center* 3.0 y *SMI BeGaze*.

La información es registrada mediante ficheros *log*, para su posterior análisis e interpretación. Se almacena gran cantidad de información como dónde está mirando una persona de forma continua, los puntos que más le llaman la atención, la velocidad de parpadeo, la ruta que han recorrido los ojos de la persona en la pantalla... [76]

Para saber más sobre esta tecnología de reconocimiento ocular es recomendable leer el artículo incluido en el documento sobre *eye-tracking* y algoritmos de selección de características [69] para profundizar en los datos registrados. Además, otro de los artículos que integran la tesis sobre el uso de la tecnología de seguimiento ocular para analizar el comportamiento de los adultos en procesos de aprendizaje [68], va acompañado de un vídeo en el que se pueden observar más características de esta tecnología.

Capítulo 2

Objetivos

Antes de presentar los publicaciones que componen esta tesis doctoral se indican los objetivos que motivaron la realización de este trabajo de investigación.

El objetivo principal del trabajo es analizar el proceso de enseñanza-aprendizaje en distintos entornos y etapas educativas, aplicando diversas técnicas de *Educational Data Mining* para la extracción de información y conocimiento.

2.1. Objetivos desglosados

1. Analizar el proceso de enseñanza-aprendizaje en distintos entornos y etapas educativas.

    a) Analizar si hay diferencias en el aprendizaje y resolución de tareas de tipo STEM en función del entorno de aprendizaje, de la variable género y de los resultados académicos de los estudiantes en los últimos cursos de Educación Primaria.

    - Estudiar si aparecen diferencias en la elección de futuras profesiones STEM vs. no STEM en función del género en etapas educativas tempranas.

    b) Analizar si existen diferencias significativas en el proceso de enseñanza-aprendizaje en función de los conocimientos en *e-Learning* del profesorado y de la modalidad de enseñanza.

    - Comprobar si la utilización de los recursos y actividades en los LMS es distinta en función del perfil del profesorado (profesor experto en *e-Learning* vs. profesor no experto).

- Estudiar si hay diferencias en la utilización de los entornos LMS por parte de los estudiantes dependiendo del tipo de profesorado, del grado que estudian (STEM vs. no STEM) y del género del estudiante.
- Comprobar la satisfacción de los estudiantes con el proceso de enseñanza y aprendizaje.

c) Analizar el proceso de enseñanza aprendizaje empleando la tecnología *eye-tracking*.

- Monitorizar el comportamiento de los usuarios (estudiantes y profesores) durante la resolución de tareas de aprendizaje autorregulado.
- Estudiar las métricas de seguimiento ocular y ver si tienen relación con el perfil del estudiante.

2. Aplicar técnicas de EDM para la extracción de información sobre el proceso de enseñanza-aprendizaje.

a) Utilizar una herramienta de análisis de registros de LMS para detectar estudiantes en riesgo en distintas etapas del curso.

b) Detectar agrupamientos de estudiantes empleando distintos algoritmos

- Comprobar si existen diferencias en los agrupamientos en función del algoritmo utilizado.
- Estudiar si conindicen los agrupamientos respecto de las interacciones en el LMS con la categorización de los grupos colaborativos y los resultados aprendizaje.

2.2. Correspondencia entre objetivos y artículos publicados

El trabajo llevado a cabo para la consecución del objetivo **1a** relacionado con el estudio del proceso de enseñanza-aprendizaje en la etapa de Educación Primaria se puede encontrar en el artículo sobre *Effectiveness of Self-Regulation and Serious Games for Learning STEM Knowledge in Primary Education* [71] en la sección 3.1.1.

El objetivo **1b**, que es muy extenso puesto que engloba el análisis de las diferencias significativas en el proceso de enseñanza-aprendizaje en función de los conocimientos en *e-Learning* del profesorado y de la modalidad de enseñanza, así como diferencias significativas entre los distintos perfiles de usuarios de los LMS se ha desarrollado en tres de los artíclulos publicados que componen esta tesis doctoral. El primer artículo se puede encontrar en la sección 3.1.2, *Teaching and Learning Styles on Moodle: An Analysis of the Effectiveness of Using STEM and Non-STEM Qualifications from a Gender Perspective* [65]. Después, en el artículo *Monitoring of Student Learning in Learning Management Systems: An Application of Educational Data Mining Techniques* [72] además del objetivo **1b** se abordan también los objetivos **2a** y **2b** que están enfocados a la aplicación de técnicas EDM para el análisis de los *logs* de información extraídos de Moodle. Por otro lado, la monitorización del proceso de enseñanza-aprendizaje que nos permiten los LMS se aborda en la sección 3.1.5 *Improve teaching with modalities and collaborative groups in an LMS: an analysis of monitoring using visualisation techniques* [61] donde se analiza el nivel de satisfacción de los estudiantes así como el objetivo **2b** sobre la coincidencia de los agrupamientos de estudiantes en función de su interacción con el LMS y sus resultados de aprendizaje.

En el artículo *Eye-tracking Technology and Data-mining Techniques used for a Behavioral Analysis of Adults engaged in Learning Processes* [68] se expone el uso de la tecnología *eye-tracking* como herramienta para analizar el proceso de enseñanza y aprendizaje que plantea el objetivo **1c**, es complejo debido a la gran cantidad de parámetros y variables que se extraen con esta técnica como también se puede comprobar en la sección 3.1.4 *Analysis of the Learning Process through Eye Tracking Technology and Feature Selection Techniques* [69] donde también se aplican técnicas EDM como expone el objetivo **2b**.

Capítulo 3

Publicaciones y Acciones de Difusión

3.1. Publicaciones Principales

A continuación, como méritos principales de esta tesis doctoral se presentan séis publicaciones todas ellas indexadas en la *Web of Science* (WOS), una publicación en Q1, cinco en Q2 y la última en Q3. Además, todas las publicaciones se encuentran también indexadas en Scopus y dos de ellas en la Clasificación Integrada de Revistas Científicas (CIRC).

3.1.1. Artículo 1: *Effectiveness of Self-Regulation and Serious Games for Learning STEM Knowledge in Primary Education*

La revista Psicothema (eISSN: 1886-144X ISSN: 0214-9915) es una revista trimestral fundada en Asturias en 1989 y está editada conjuntamente por la Facultad de Psicología de la Universidad de Oviedo y el Colegio Oficial de Psicólogos del Principado de Asturias. Su calidad y prestigio internacional hizo que fuese de las primeras revistas españolas de Ciencias Sociales en ser indexada en *Social Science Citation Index* (SSCI), en el año 1993.

La investigación llevada a cabo y asociada a este artículo ha sido financiada con la beca EDUCYL2018_04 concedida por la Consejería de Educación de la Junta de Castilla y León a través de la Dirección General de Innovación y Equidad Educativa, bajo el proyecto "Igualdad de género en materias científico-tecnológicas: análisis comparativo de estudiantes STEM".

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Effectiveness of Self-Regulation and Serious Games for Learning STEM Knowledge in Primary Education

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Universidad de Burgos

Abstract

Background: The learning of scientific and technological subjects is fundamental in the society of the 21st century. However, a gender gap is detected in the choice of degrees in these subjects. Recent studies indicate the need to take action from the primary education stage to increase student motivation towards these disciplines. **Methods:** We worked with a sample of 147 students in the final years of Primary Education. SRL and serious games were applied in initial tasks to computer programming. The objectives were to study the influence of gender, environment and academic level variables on the results in the resolution of initial programming tasks and on student satisfaction with their completion. **Results:** The mean level of results in these tasks was high (8 out of 10). However, significant differences were found for gender, academic level, and the age covariates. With respect to satisfaction, no significant differences were found except in the continuity of work. **Conclusions:** The use of SRL and serious play tasks promotes good levels of performance and satisfaction in all students, although differences in favour of the male gender are detected.

Keywords: serious games, self-regulated learning, STEM, gender, satisfaction, computer programming.

Resumen

Efectividad de la Autorregulación y los Serious Games Para el Aprendizaje de Conocimientos STEM en Educación Primaria. **Antecedentes:** el aprendizaje de materias científico-tecnológicas es fundamental en la sociedad del s. XXI. Si bien, se detecta una brecha de género en la elección de titulaciones en estas materias. Estudios recientes indican la necesidad de realizar acciones desde la etapa de Educación Primaria para aumentar la motivación de los estudiantes hacia estas disciplinas. **Método:** se trabajó con una muestra de 147 estudiantes de los últimos cursos de Educación Primaria. Se aplicó SRL y serious games en tareas de inicio a la programación informática. Los objetivos fueron estudiar la influencia de las variables género, entorno y nivel académico sobre los resultados en la resolución de tareas de inicio a la programación y en la satisfacción de los estudiantes con su realización. **Resultados:** el nivel medio de resultados en estas tareas fue alto (8 sobre 10). Sin embargo, se hallaron diferencias significativas respecto de las variables género, nivel académico y efectos de la covariable edad. Relativo de la satisfacción no se hallaron diferencias significativas salvo en la continuidad de trabajo. **Conclusiones:** la utilización de SRL y de tareas de juego serios potencia buenos niveles de rendimiento y de satisfacción en todos los estudiantes, aunque se detectan diferencias a favor del género masculino.

Palabras clave: serious games, self-regulated learning, STEM, género, satisfacción, lenguaje de programación.

In 21st century society, education authorities have shown great interest in the enhancement of STEM (Science, Technology, Engineering and Mathematics) subjects (Stehle & Peters-Burton, 2019; Queiruga-Dios et al., 2020). The UNESCO report (Bokova, 2018) proposed a model citizen who, by 2030, will have transformative, innovative and creative thinking and skills within a digital society in situations of gender equality. This report revealed that in the 10-11 age group, boys and girls were equally committed to STEM subjects (75% and 72%, respectively). However, by the age of 18 this proportion fell to 33% for boys and 19% for girls. There is therefore a decline in the interest shown in the female gender. Subsequently, in Higher Education, the gap in the percentage of enrolment in engineering, technology, construction and computer science degrees increased for men and decreased for women (72% vs. 28%). However, the proportion tends to be equal (55% women vs. 45% men) in mathematics and statistical science degrees. It is therefore necessary to investigate the causes for this choice and its relation to the gender gap in the educational stage prior to Secondary Education.

Recent studies have shown that the gender gap already begins in Primary Education (García-Holgado, Verdugo-Castro et al., 2019). These authors recommend using forms of teaching based on experimentation. The aim is to increase motivation and improve execution, in order to try to equalize the percentages of choice between boys and girls. Regarding this objective, it has been found that the use of tasks that include gamification increases student motivation towards participation (Troiano et al., 2019). Gamification is a new concept that involves the use of what has been called serious games. These are games in which actions or

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activities of reflection on a task are included. One of the reasons for their effectiveness is that they facilitate the development of metacognitive strategies of orientation and planning during the resolution of tasks (Cloude et al., 2019). These tasks have a very structured design based on a sequential order of difficulty. In addition, they include the guidance of an avatar that guides the user's learning through verbal aids and/or examples that promote Self-regulated learning (SRL) (Cerezo et al., 2010; Taub et al., 2014). This type of methodology is inserted within Advanced Learning Technologies (ALTs). Techniques that include the analysis of the user's learning process, since they record and monitor the development of the resolution within a learning loop that increases learner motivation (Zimmerman & Moylan, 2009). The objective is to promote interactive learning through a simulation structure in which aids are introduced that may be verbal, visual, or both (Patti, 2019). They must however include a precise narrative design of the activity accompanied by good technical skills, in order for serious games to produce an increase in the learners' creativity and motivation (Kretschmer & Terharen, 2019). Similarly, the use of serious games in natural teaching contexts has been shown to increase student motivation towards STEM-type tasks (Alsawaier, 2018; Bovermann & Bastiaens, 2020; Dreimane, 2019). Therefore, recent research has concluded that its use is an excellent resource in the educational context (Nogueira-Frazão & Martínez-Solana, 2019). In this way, Gallego-Durán et al. (2014) carried out a meta-analysis study that analyzed traditional teaching techniques vs. gamma teaching. These authors found that variables such as age, task type, reaction time, attention levels and motivation, among other variables, influenced learning processes. Likewise, these authors found that gamma teaching explained 72% of the variance in learning outcomes, with 45% of those outcomes specifically explained by gamma maze and puzzle tasks.

In summary, the use of serious game tasks (Clark, 1970) encourages the learner to experiment, access feedback, SRL and reduces the fear of error by increasing motivation to learn (Contreras et al., 2019). Hence, the implementation of serious games in teaching offers a current and efficient alternative to traditional teaching-learning methods. In Figure 1, an example of the work with serious games applied to learning at the beginning of programming is presented. A resource known as Blockly Games is used for this serious game, because it is an easy to use the tool on the web with free access. In addition, Blockly Games includes the figure of an avatar that guides the resolution of the tasks and that gives feedback to the student on the errors and successes during the execution.

The use of SRL also facilitates process-oriented feedback (Brooks et al., 2019; Coertjens, 2018; Hattie & Clarke, 2018; Park et al., 2019). The use of such feedback provides the learner with the opportunity to understand what is being done and what it is being done for, which enhances their autonomy in learning (Lodge et al., 2018; Sáiz-Manzanares et al., 2019). The use of this methodology in the teaching of STEM subjects has been shown to be very effective in achieving effective learning and increasing motivation (Taub et al., 2018; Zheng et al., 2020). Recent studies (Díaz-Lauzurica & Moreno-Salinas, 2019; Kintsakis & Rangoussi, 2019) have shown that the inclusion of gamma tasks in STEM subjects, specifically those related to the learning of programming skills, increases the motivation of students to perform them and improves their results. In addition, the motivation is extended to the teacher, which promotes a very effective loop between both agents (teacher-student) (Cerezo et al., 2018). The most widely used resources to teach the initial stages of programming use Scratch [Scratch is a visual programming language developed by the Lifelong Kindergarten Group of the MIT Media Lab (Marji, 2014). Its main feature is to enhance the learning of computer programming without having an in-depth knowledge of the code. Its features linked to the easy understanding of computer thinking have made it very widespread in the education of children, adolescents and adults)] and Blockly Games (Blockly Games contains a series of educational games that teach programming. It is designed for children who do not have previous experience in computer programming tasks).

In summary, the design of STEM tasks specifically in a programming language which includes SRL and serious games is of great interest to the researcher (Tucker-Raymond et al., 2019), because it can be used to visualize the application of various and especially metacognitive learning strategies during the process of solving these tasks (Sáiz-Manzanares & Marticorena-Sánchez,

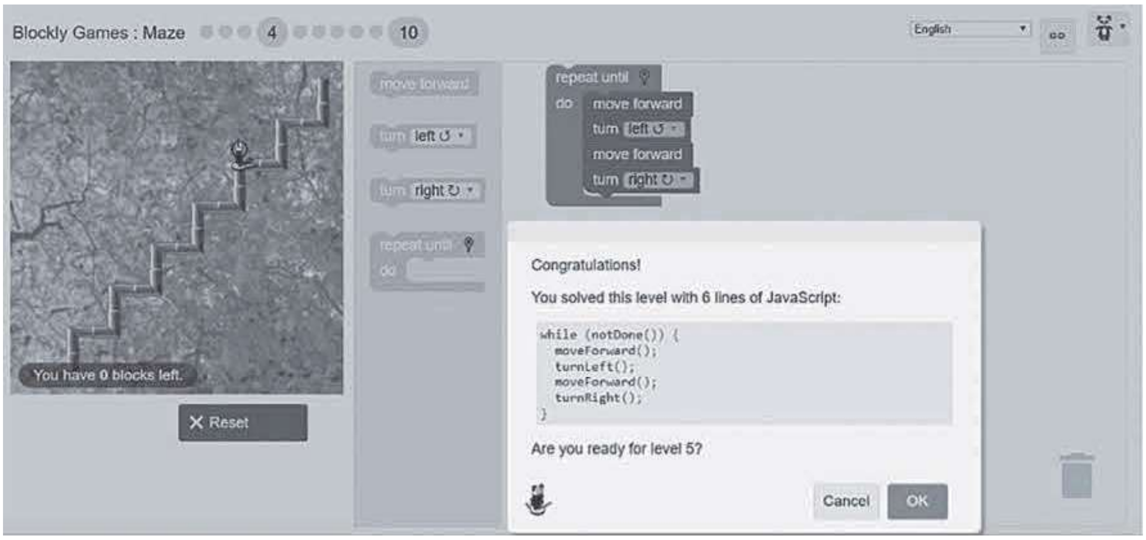


Figure 1. Example of serious games using Blockly Games

2016; Stehle & Peters-Burton, 2019; Zainal et al., 2018). In relation to this last aspect, research is currently underway to facilitate the study of the implementation of STEM experiences. These studies include the RoboSTEM project (García-Holgado, Camacho-Díaz et al., 2019) and the W-STEM project (Conde-González et al., 2019; García-Peñalvo et al., 2019). Both projects stress the need to apply the teaching of STEM subjects in natural contexts at all levels of the education system.

In view of the above, the objectives of this study were: 1) to analyse whether there were significant differences in the results obtained in the resolution of initial programming tasks with respect to the independent variables of gender, learning environment and academic level, and the covariate of age; 2) to analyse whether there were significant differences in student satisfaction with the execution of initial programming tasks in relation to the independent variables of gender, learning environment and academic level, and the covariate of age.

To answer these objectives, the following research questions were posed:

RQ1. There will be significant differences in the level of execution in tasks of initiation to computer programming carried out with serious games depending on the independent variables gender (boys vs. girls), learning environment (regular classroom vs. computer classroom) and academic year (5th vs. 6th), and the covariate age.

RQ2. There will be significant differences in student satisfaction with the execution of initial tasks to computer programming performed with serious games depending on the independent variables gender (boys vs. girls), learning environment (regular classroom vs. computer classroom), academic year (5th vs. 6th), and the covariate age.

Method

Participants

We worked with a sample of 147 students (76 boys and 71 girls) in Primary Education at the 5th and 6th grade academic levels. The characteristics of the sample can be seen in Table 1. Convenience sampling was used for the selection of the sample from educational centres whose students shared similar socioeconomic characteristics and belonged to the same city in the north of Spain.

Instruments

Blockly Games maze task. Blockly Games is a free web application that includes a series of educational games aimed at teaching programming. It is designed for children with no previous experience neither of the use of code, nor in computer programming tasks. When the execution of these games is finished, the players are ready to use the conventional text-based programming languages.

Table 1
Descriptive statistics of the participants

			Center 1					Center 2					
Academic level	N	n	Children		n	Girls		n	Children		Girls		n
			M	SD		M (d)	SD (d)		M	SD (d)	M	SD (d)	
5º	85	20	10.05	.39	24	10.17	.38	22	10.31	.57	10.21	.63	19
6º	62	24	11.04	.46	20	11.00	.45	10	11.30	.67	11	.00	8
Total	147	44			44			32					27

Note: *N* = total number of students; *n* = partial number of students; *M* = Mean average age; *SD* = age standard deviation

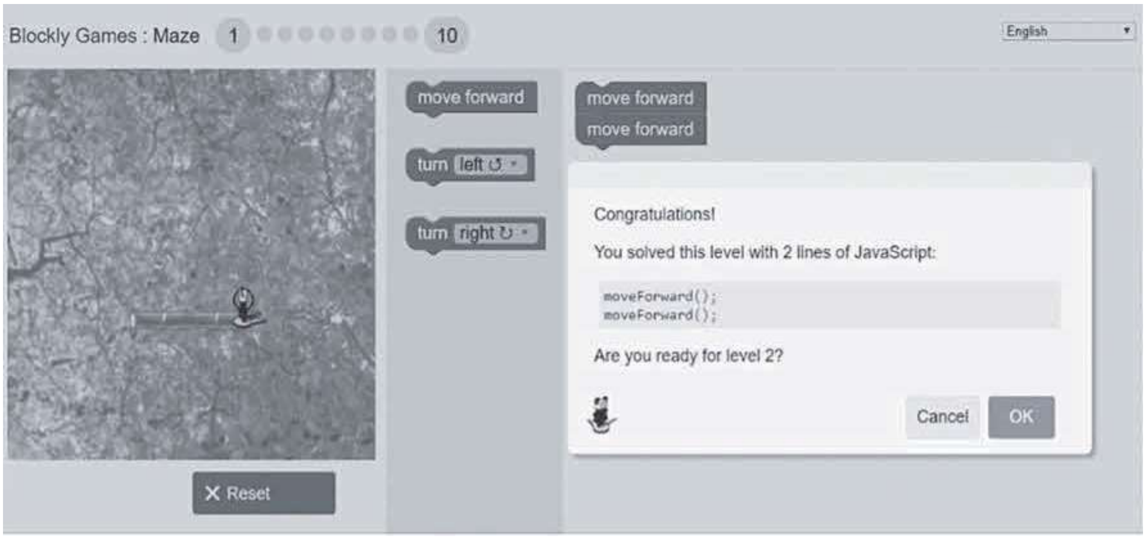


Figure 2. Feedback after completing Blockly Games maze task on level 1

Specifically, the maze task consists of solving different mazes that have degrees of increasing difficulty from 1 to 10. In such tasks, the participant can choose the type of avatar with which he will play the game (a panda bear, an astronaut or an impersonal figure). Also, before executing the activity, the trainee has to think about how it may be solved. After each game the participant receives feedback on the outcome of the execution. If the answer is correct, the programming syntax that the participant has implemented will be returned. An example of how this functions can be seen in Figure 2.

Self-regulating instruction. In all intervention groups, self-regulated instruction was applied, which consisted of asking students task-oriented questions. Both declarative (related to the conceptual content of the task) and procedural (related to the planning of the resolution) metacognitive skills are used in this sort of such instruction. An example of the thinking aloud dialogue with SRL can be seen in Table 2.

Student satisfaction survey with the Blockly Games maze workshop. This instrument is an adaptation of the survey developed by Appianing and Van Eck (2018) (see Table 3), the instrument has a reliability index of α = .90. The adapted survey consists of 5 items measured on a Likert-type scale from 1 (total disagreement) to 5 (total agreement). The first question refers to whether the student has carried out similar activities and is considered as an analysis of previous knowledge.

Procedure

Prior to the start of the research, the authorization of the Bioethics Committee of the University of Burgos was obtained (IR 19/2018), as well as the authorization of the heads of the Department of Education of the Junta de Castilla y León and the educational centres where the research was carried out. Similarly, written informed commitment was obtained from the parents or legal guardians of all the students participating in the study. Afterwards, the Blockly Games labyrinth task was worked on in the 5th and 6th grades of Primary Education. Labyrinths consists of 10 games in which students have to solve different mazes graduated in order of difficulty. At the beginning of the game, the figure of an avatar is chosen that will accompany the student during the resolution, the duration of each intervention was of one hour.

The distribution of teachers at each of the centres was respected, so the work was carried out in two environments. Environment 1: computer classroom with PC (number of students from 10 to 12) and Environment 2: ordinary classroom with Mini-PC (number of students from 21 to 25). In both environments, SRL methodology was applied. The instruction was carried out by two teachers from outside the centre, one specialised in Computer Science and the other in Psychology of Instruction.

Data analysis

A 2×2×2 factorial design was used [gender (male vs. female), learning environment (regular classroom vs. computer classroom) and academic year (5th vs. 6th)]. The dependent variables were the results in the serious games tasks (Blockly Games) and student satisfaction with them. First, a normality analysis of the sample was performed (for which asymmetry and kurtosis indicators were used), followed by an ANOVA to check whether the students from the centres were equal in the previous knowledge variable. Finally, a three-factor ANCOVA and a covariate were applied, in order to contrast the research questions, and an analysis of the value of the effect was also performed, using eta-squared (η^2). All the analyses were performed with the SPSS v.24 statistical package and a 95% confidence interval was applied.

Results

Firstly, we studied the homogeneity between the students of the two participating centres with respect to the background knowledge variable. No significant differences were found between the students of the two centres, $F(1, 147) = .00$, $p = .99$ ($\eta^2 = .00$). We then studied whether the sample met the standards of normality. To do so, the values of asymmetry and kurtosis with respect to previous knowledge were found. As can be seen in Table 4, no deviations were found in the normal values [acceptable asymmetry values should be no higher than |2.00| and those of kurtosis should not be within the interval between |8|-|20| (Bandalos & Finney, 2001). Based on the results, we used parametric statistics to test the research questions.

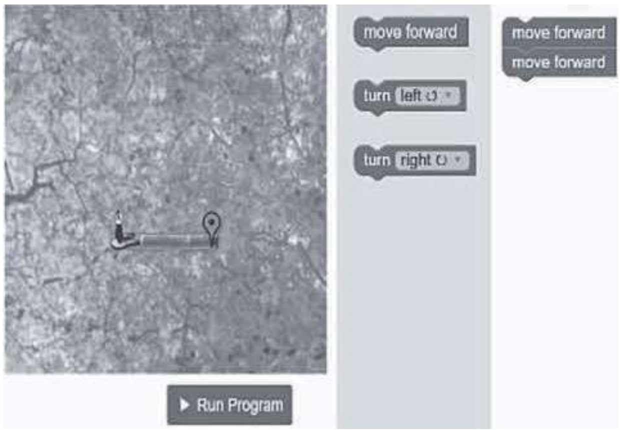
An ANCOVA with three fixed-effect factors (gender, learning environment, and academic level) was used to test RQ1, with age considered to be a covariate. Significant differences were found in the results of the execution of the Blockly Games tasks with respect to the gender variable $F(1, 147) = 4.92$, $p = .03$ ($\eta^2 =. 03$). Also, differences were found with the variable 'academic level' $F(1, 147) = 8.15$, $p = .01$ ($\eta^2 = .06$) and the age covariate $F(1, 147) = 6.70$, $p = .01$ ($\eta^2 = .05$). In contrast, no significant differences were found regarding the variable 'learning environment'. It is important to point out that the highest means for the maze task resolution were found in setting 1 among 6th grade children (M = 8.40) and in setting 2 among 5th grade children (M = 8.31) and 6th grade children (M = 8.42) (see Table 5).

An ANCOVA with three fixed-effect factors (gender, learning environment and academic level) was used to compare RQ2, with age as a covariate. With respect to the gender and environment variables, no significant differences were found in student satisfaction with the execution of Blockly Games tasks. Regarding the academic level variable, differences were found in satisfaction, specifically in item 3 which referred to the student's motivation to continue performing this type of task $F(1, 147) = 8.15$, $p = .01$ ($\eta^2 = 0.06$). The highest Means were found in setting 1 among boys in 5th grade (M = 5.00) and 6th grade (M = 4.90) and among girls in 6th grade (M = 5.00) (see Table 5).

Discussion

Virtual Learning Environments (VLEs), specifically those using the serious games technique (Liu & Liu, 2020) implemented in conjunction with SRL (Taub et al., 2014) facilitate self-regulated instruction and increase student performance (Cloude, 2019; Veenman et al., 2014). The use of this methodology has been shown to be very effective for the instruction of STEM subjects (Alsawaier, 2018; Bovermann & Bastiaens, 2020; Dreimane, 2019; Queiruga et al., 2020; Sáiz-Manzanares & Marticorena-Sánchez, 2016; Zainal, 2018). In line with the conclusions of these investigations, the results of this study indicate that the performance of students in tasks of initiation to computer programming, in which both serious games (Blockly Games) and

Table 2
Example of a self-regulating dialogue in the resolution of the Blockly Games maze task on level 1

Teacher	Task resolution strategies	Dialogues, task resolution modeling
Defining task 1	"You have to choose the avatar of your choice (the Panda Bear, the astronaut or the person) reach the goal."	
Resolution-oriented strategies	"What do we have to do?"	"In this task the panda bear has to go straight on to reach the goal."
Task resolution planning strategies	"How are we going to do it?"	"For the panda bear to go straight on, you just have to use the forward block a couple of times. As you can see, we take the block and join it twice, then press run program and the avatar reaches the goal. Bravo, we have solved the first maze." "Let's start"
Resolution process evaluation strategies	"How are we solving the maze?"	
		
	"We have to learn the code"	"Look this is the code, it just means we move forward the panda bear and we have to do it twice" moveForward(); moveForward();

SRL are applied, has been very satisfactory among both boys and girls (Mean of 8 out of 10). However, performance was higher in boys. These results, on the one hand, support the theory that the combined use of SRL with serious games increases students' motivation to approach these subjects through play (Cerezo et al., 2010; Contreras et al., 2019; Díaz-Lauzurica & Moreno-Salinas, 2019; Taub et al., 2014; Zheng et al., 2020; Zimmerman & Moylan, 2009). The possible causes are that this methodology implements the use of simulation (Patti, 2019) together with the use of the figure of an avatar (Taub et al., 2014) that provides feedback on the execution, which facilitates an avoidance of the fear of error (Brooks et al., 2019; Coertjens, 2018; Conteras et al., 2019; Hattie & Clarke, 2018; Park et al., 2019) from a graduation of difficulty in the presentation of tasks (Cherry et al., 2019; Kretschmer & Terharen, 2019; Patti, 2019; Sáiz et al., 2019). However, this study found a difference in performance in Blockly Games in favor of the male gender, which supports the findings of the studies by García-Holgado et al. (2019), indicating that gender differences begin before secondary education. The degree of satisfaction of students with the performance of tasks at the beginning of the programming in Blockly Games yielded very satisfactory results among boys and girls, however more motivation to continue working on similar activities was observed among boys rather than girls.

On the other hand, it seems that the place where the activity is implemented is not significant in terms of performance or student satisfaction. Where differences have been found is with respect to the academic level variable and the age covariate. This aspect can be explained from the hypothesis that up to the age of 11, boys and girls would have a similar behaviour towards the execution of STEM tasks (Bokova, 2018). However, at the age of 11, this difference may already be starting to appear (it should be taken into account that in 6th grade of Primary Education there are students who are older than 11). This coincides with the findings of studies by Verdugo-Castro et al., (2019) that the gender gap already begins in Primary Education. It leads to a necessary reflection on the part of educationalists on what can happen for this change to take place; possible explanations could be related to the influence of variables such as: the learning history of students, the teaching style of the teacher, the upbringing style of families or other factors related to the social and/or family environment of boys and girls (Brooks et al., 2019; Gallego-Durán et al., 2014). Therefore, future research will be aimed at studying the effect of these variables and checking whether there are differences between boys and girls.

Finally, although the results found in this study are in line with those found in the research that has supported it, these results should be treated with caution, taking into account the characteristics of the sample and the time of instruction applied.

In summary, more research is needed on this topic that provides representative data when conducted in natural learning contexts (Girvan & Savage, 2019; Queiruga et al., 2020; Sáiz-Manzanares et al., 2019). The ultimate goal is for them to serve educational leaders in governments and institutions as a basis for decision-making on the design of instruction in STEM subjects at each stage of the education system (Stehle & Peters-Burton, 2019), in order to overcome the gender gap and ensure digital literacy in society. In this regard, it is important to note that STEM subjects, specifically those related to learning computer programming in the stages prior to Secondary Education, are not explicitly part of the curricula. It is a fact highlighted in many research projects (Conde-González et al., 2019; García-Holgado, Camacho-Díaz et al., 2019; García-Peñalvo, 2019), upon the premise of enhancing STEM teaching in regular teaching-learning environments, since the society of the 21st century requires digital literacy for the entire population (Azevedo & Gašević, 2019; Cloude et al., 2019; Taub et al., 2018) that must begin in the initial years of schooling (Stehle & Peters-Burton, 2019).

Table 3
Student satisfaction survey with Blockly games maze workshop, adapted from Appianing and Van Eck (2018)

NAME:	SURNAME:					
ID CODE:	AGE:					
GENDER:	COURSE:					
LEVEL:	CENTER:					
Closed responses are measured on a Likert-type scale of 1 to 5 where 1 is not at all, never or nothing and 5 is always, fully or strongly, in agreement.						
Gradation scale		**1**	**2**	**3**	**4**	**5**
1. I had already done similar activities.		1	2	3	4	5
2. I found the activity interesting.		1	2	3	4	5
3. I would like to do more of these activities.		1	2	3	4	5
4. I understood what had to be done in the activity.		1	2	3	4	5
5. I liked the activity because I worked with other colleagues.		1	2	3	4	5

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Table 4
Indicators of asymmetry and kurtosis in the pre-knowledge variable

	N	**Minimum**	**Maximum**	**M**	**SD**	**Asymmetry**	**SEA**	**Kurtosis**	**SEK**
Previous knowledge	147	1	5	2.66	1.69	0.33	0.20	-1.61	0.40

Note: *N* = number of students; *M* = Mean; *SD* = Standard Deviation; *SEA* = Standard Error *Asymmetry*; *SEK* = Standard Error Kurtosis

Table 5
ANCOVA with three fixed-effect variables (gender, learning environment, and academic level) and covariate age

	Environment 1 n = 43				**Environment 2 n = 104**				$F_{(1, 147)}$	p	η2
	Child n = 20		**Girl n = 23**		**Child n = 56**		**Girl n = 48**				
	5º	**6º**	**5º**	**6º**	**5º**	**6º**	**5º**	**6º**			
	n = 10	**n = 10**	**n = 11**	**n = 12**	**n = 32**	**n = 24**	**n = 32**	**n = 16**			
	M(SD)	**M(SD)**	**M(SD)**	**M(SD)**	**M(SD)**	**M(SD)**	**M(SD)**	**M(SD)**			
Independent variable gender											
Results in Blocking Games	8.00(1.41)	8.40(1.50)	7.18(1.60)	8.25(1.29)	8.31(1.44)	8.42(1.31)	7.59(1.81)	7.75(1.61)	4.92	.03*	.03
2	4.10(1.66)	4.60(.70)	4.55(1.24)	4.75(.62)	4.59(.84)	4.67(.57)	4.81(.74)	4.63(.74)	1.38	.24	.01
3	5.00(.00)	4.90(.32)	4.64(1.21)	5.00(.00)	4.75(.51)	4.83(.64)	4.47(1.22)	4.63(.62)	2.16	.14	.02
4	4.40(1.08)	4.50(.97)	4.27(1.27)	4.58(.67)	4.78(.49)	4.75(.53)	4.63(.79)	4.69(.60)	0.25	.62	.002
5	4.70(.68)	4.50(1.27)	4.36(1.30)	4.25(1.21)	4.56(.91)	3.92(1.25)	4.78(.55)	4.44(1.03)	0.03	.86	.00
Environmentally independent variable											
Results in Blocking Games									0.14	.72	.00
2									150	.22	.01
3									1.81	.18	.01
4									4.02	.05	.03
5									0.01	.93	.00
Independent variable level											
Results in Blocking Games									8.15	.01*	.06
2									3.21	.08	.02
3									7.35	.01*	.05
4									1.23	.27	.01
5									0.51	.48	.004
Covariate age											
Results in Blocking Games									6.70	.01*	.05
1									2.79	.10	.02
3									9.93	.002	.07
4									0.60	.44	.004
5									1.05	.31	.01

Note: *M* = Mean; *SD* = Standard deviation; 2 = I found the activity interesting; 3 = I would like to do more activities of this type; 4 = I understood what to do in the activity; 5 = I liked the activity, because I worked with other colleagues.
* $p < .05$

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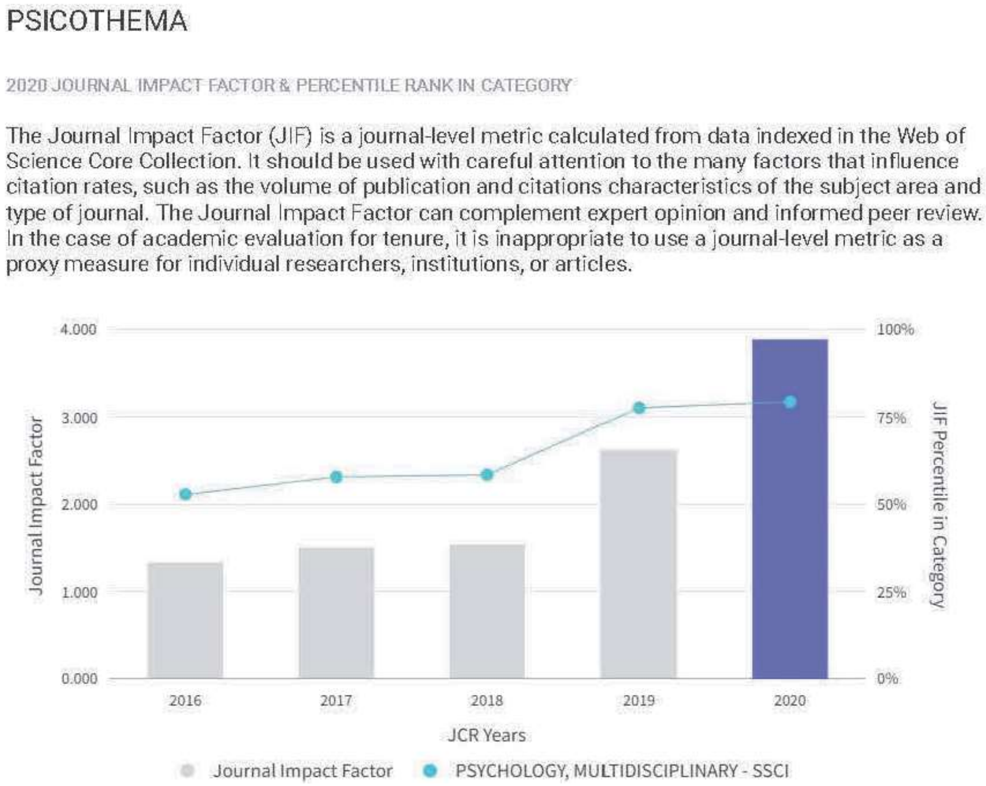

Figura 3.1: JIF Revista *Psicothema* 1. Fuente: WOS (31/08/2021)

3.1.1.1. Estándares de calidad de la revista *Psicothema*

La revista *Psicothema* está indexada en la base de datos *Social Sciences Citation Index* (SSCI), dentro de la categoría *PSYCHOLOGY, MULTIDISCIPLINARY – SSCI*. En el último registro, año 2020, tiene un *Journal Impact Factor* (JIF) de 3.890 y un *Journal Impact Factor Without Self Citations* de 3.354. En el año de publicación del artículo, 2020, se situaba en la posición 29 de 140 revistas, es decir en el primer cuartil (Q1). Veánse las imágenes 3.1 y 3.2.

Psicothema está también indexada en Scopus (Elsevier) desde 1996 (indexación retrospectiva). En el año 2011 presenta un valor en el SJR (indicador análogo al Factor de Impacto) de 0,64, lo que la sitúa en la posición 47 de un total de 2245 revistas en la disciplina de *PSYCHOLOGY (MISCELLANEOUS)*. Tiene un H *index* de 47.

PSICOTHEMA

2020 JOURNAL IMPACT FACTOR & PERCENTILE RANK IN CATEGORY

The Journal Impact Factor (JIF) is a journal-level metric calculated from data indexed in the Web of Science Core Collection. It should be used with careful attention to the many factors that influence citation rates, such as the volume of publication and citations characteristics of the subject area and type of journal. The Journal Impact Factor can complement expert opinion and informed peer review. In the case of academic evaluation for tenure, it is inappropriate to use a journal-level metric as a proxy measure for individual researchers, institutions, or articles.

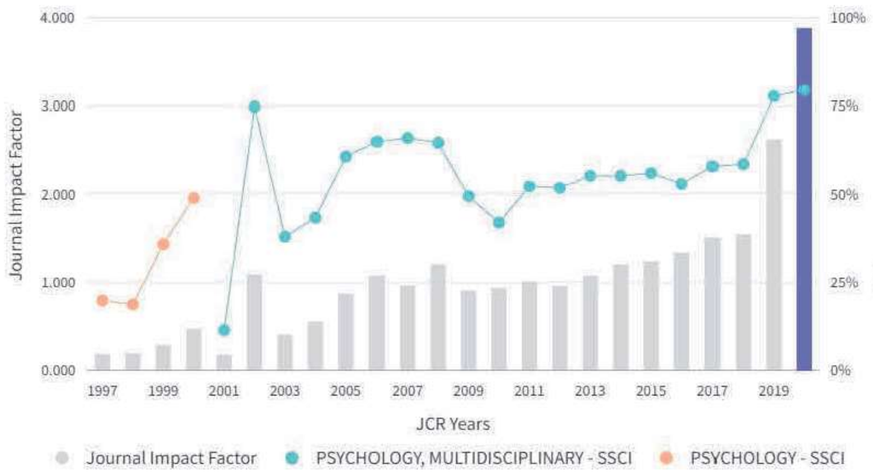

Figura 3.2: JIF Revista *Psicothema* 2. Fuente: WOS (31/08/2021)

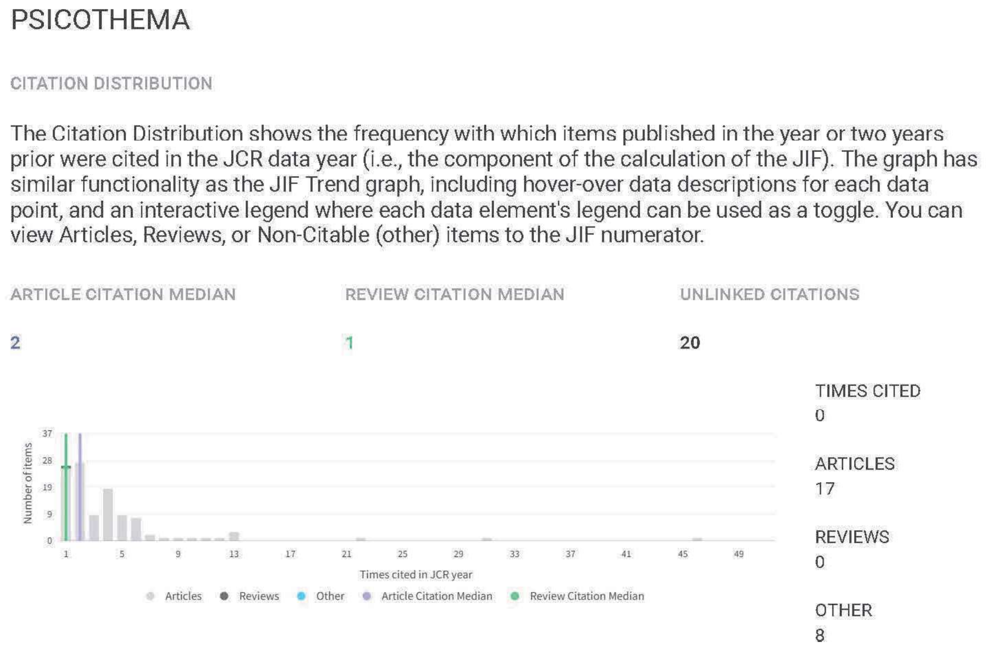

Figura 3.3: Citaciones Revista *Psicothema*. Fuente: WOS (31/08/2021)

3.1.1.2. Estándares de calidad del artículo 1

A finales de julio del año 2021 este artículo contaba con 46 citaciones en la base de datos de la *Web Of Science* y siendo la media de citas de la revista 2 como puede verse en las imágenes 3.3 y 3.4.

3.1.2. Artículo 2: *Teaching and Learning Styles on Moodle: An Analysis of theEffectiveness of Using STEM and Non-STEM Qualificationsfrom a Gender Perspective*

Sustainability (ISSN 2071-1050) es una revista internacional, interdisciplinaria, académica, de acceso abierto y revisada por pares, sobre la sostenibilidad ambiental, cultural, económica y social de los seres humanos. *Sustainability* proporciona un foro avanzado para estudios relacionados con la sostenibilidad y el desarrollo sostenible, y es publicada semestralmente en línea por el MDPI. El acceso es gratuito para los lectores, y los gastos de procesamiento de los artículos (APC) corren a cargo de los autores o de sus

Figura 3.4: Citaciones del artículo 1. Fuente: WOS (31/08/2021)

instituciones.

Las publicaciones son rápidas, los manuscritos son revisados por pares y se proporciona una primera decisión a los autores aproximadamente 17 días después de su presentación; la aceptación de la publicación se realiza en 3,6 días (valores medianos para los artículos publicados en esta revista en el segundo semestre de 2019). La revista cuenta con una alta visibilidad al estar indexada en la WOS (*Science Citation Index Expanded* y el *Social Sciences Citation Index*), en Scopus y en otras bases de datos.

Este artículo y la investigación se ha costeado con la beca BU032G19 concedida por la Consejería de Educación de la Junta de Castilla y León y becas concedidas por el Vicerrectorado de Personal Docente e Investigador y el Vicerrectorado de Investigación y Transferencia del Conocimiento de la Universidad de Burgos para la difusión de experiencias de innovación y mejora de la docencia durante el año 2020.

3.1.2.1. Estándares de calidad de la revista *Sustainability*

Sustainability (ISSN 2071-1050) es una revista indexada en la *Web Of Science*. Se encuentra en la base de datos Journal Citation Report, dentro de la categoría *ENVIRONMENTAL STUDIES – SSCI* donde se encuentra en el segundo cuartil (Q2 JIF = 52.40). En el año 2020, en el momento en el que se publicó la aportación, la revista se situó en la posición 60 de 125 revistas en un Q2 con un *Journal Impact Factor* (JIF) de 3.251 y un *Journal Impact Factor Without Self Citations* de 2.355. En ESI en 2018 (último dato registrado en WOS) ocupa una posición de 37 entre un total de 370 revistas, lo que la sitúa en el primer cuartil (Q1) (Ver imagen 3.5).

La revista *Sustainability* también está indexada en Scopus. La revista comienza a indexarse en 2009 en categorías de *Sustainability and Environment*. En 2018 registra un valor SJR (*Scimago Journal Rank*) de 1 =0.55, situándose en el segundo cuartil de ambas categorías, actualmente tiene un H *index* de 53. Ver: `https://www.scimagojr.com/journalsearch.php?q=144989&tip=sid&clean=0`.

Esta revista también está indexada en la Clasificación CIRC (Clasificación Integrada de Revistas Científicas), y clasificada como grupo A+. En esta base de datos el grupo de revistas clasificadas como A está "integrado por las revistas científicas de mayor nivel. Pertenecerían al mismo las revistas internacionales de mayor prestigio que han superado procesos de evaluación muy exigentes para el ingreso en diferentes bases de datos" según el comité de expertos en evaluación científica.

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Teaching and Learning Styles on Moodle: An Analysis of the Effectiveness of Using STEM and Non-STEM Qualifications from a Gender Perspective

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Abstract: Teaching in Higher Education is with increasing frequency completed within a Learning Management System (LMS) environment in the Blended Learning modality. The use of learning objects (activities and resources) offered by LMS means that both teachers and students require training. In addition, gender differences relating to the number of students in STEM (Science, Technology, Engineering, and Mathematics) and Non-STEM courses might have some influence on the use of those learning objects. The study involves 13 teachers (6 experts in e-Learning and 7 non-experts) on 13 academic courses (4 STEM and 9 Non-STEM) and a detailed examination of the logs of 626 students downloaded from the Moodle platform. Our objectives are: (1) To confirm whether significant differences may be found in relation to the use of learning objects (resources and activities) on Moodle, depending on the expertise of the teacher (expert vs. non-expert in e-Learning); (2) To confirm whether there are significant differences between students regarding their use of learning objects, depending on the expertise of the teacher (expert vs. non-expert in e-Learning); (3) To confirm whether there are significant differences for the use of learning objects among students as a function of gender. Differences were found in the use of Moodle learning objects (resources and activities) for teachers and for students depending on the expertise of the teacher. Likewise, differences were found for the use of some learning objects as a function of gender and the degrees that the students were following. Increased technological training for both teachers and students is proposed, especially on Non-STEM qualifications, in order to mitigate the effects of the technological gap and its collateral relation with the gender gap and the digital divide.

Keywords: learning styles; teaching styles; Moodle; blended learning; learning-objects; gender gap; digital gap

1. Introduction

Teaching is increasingly performed with greater frequency in digital environments known as Learning Management Systems (LMS). This form of teaching, especially significant in the context of higher education, has expanded due to the effects of the COVID-19 health crisis [1]. All these aspects mean that greater investigation is necessary into what sort of teaching is imparted and what sort of learning is developed in those environments.

The above-mentioned aspects are at present very relevant because of their direct relation with sustainability in the field of education. The training of both teachers and students in an educational context and in an increasingly digitalized society is fundamental to overcoming gender [2,3] and to achieve a sustainable society. It is all understood to take place within life-long education, as is proposed in Agenda 2030 [4] and it is precisely this challenge that educational authorities face, especially in Higher Education [5]. Early intervention in these aspects will facilitate the achievement of an increasingly sustainable society [6] and will surmount both the gender gap and the digital divide. All of this will bring with its greater opportunities and well-balanced choices of professional careers, which will imply equilibrium at work in the future within all knowledge areas [7]. In what follows, the key aspects of teaching in Blended Learning and e-Learning environments will be approached within the framework of Higher Education through an analysis of the situation with its possible gender gaps and digital divides.

A first aspect to consider is that the mere use of LMS will not in itself ensure effective teaching. Effectiveness appears to depend on what learning objects (resources and activities) are used and the way that they are implemented within a particular group of students [2,8]. Among the tools that LMS offers, some have shown themselves more effective than others, depending on the type of student and the characteristics of the content to be learned [9]. It is necessary to study the type of learning object that is applied and its usability for a student or group of students [10]. The results of this investigation highlight the personalization of the teaching proposal as a key to successful teaching-learning processes in on-line teaching environments [11]. This fact implies that the teacher has to use various learning objects within the LMS in order to provide a response to the learning needs of each student. Hence, the need, first of all, is to study the possibilities that LMSs have to offer. For example, an LMS similar to Moodle (Modular Object-Oriented Dynamic Learning Environment) offers two teaching possibilities: resources and activities [12], which facilitate interaction between teacher and students, the students themselves, and the students with the resources and activities [13]. The resources refer to “objects” (in Information Technology (IT) terms) that a teacher can use as assistance in the teaching–learning process. A description of Moodle resources may be consulted in Table A1 (Appendix A). Likewise, Moodle offers activities that are tasks that the student can complete alone or in interaction with other companions. The tasks can be evaluated and the teacher can provide feedback both on the product and on the problem-solving processes of a student or group of students (see Table A1). In Figure 1 the resources and in Figure 2 the activities that Moodle offers are shown, including some from the personalized Moodle platform for the University of Burgos (UBUVirtual).

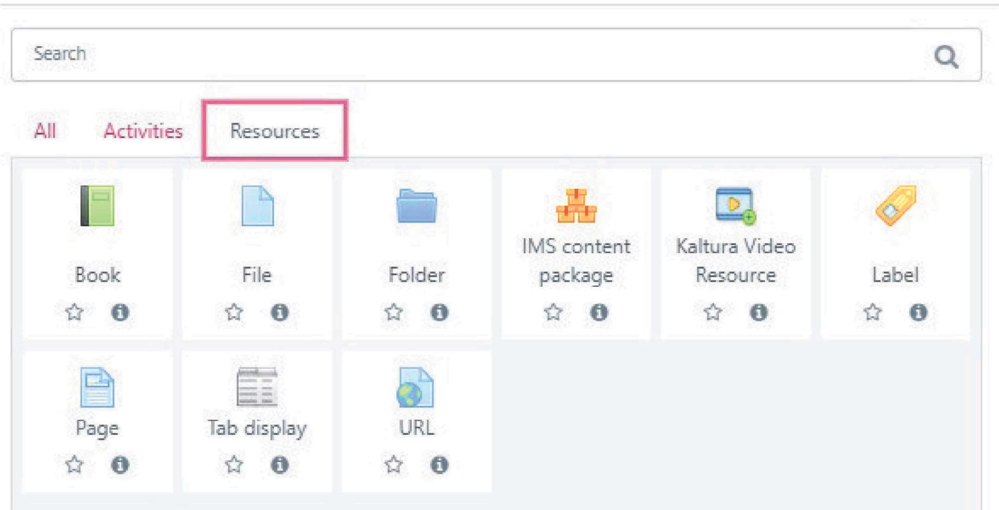

Figure 1. Resources that Moodle offers in the v. 3.8 on UBUVirtual platform.

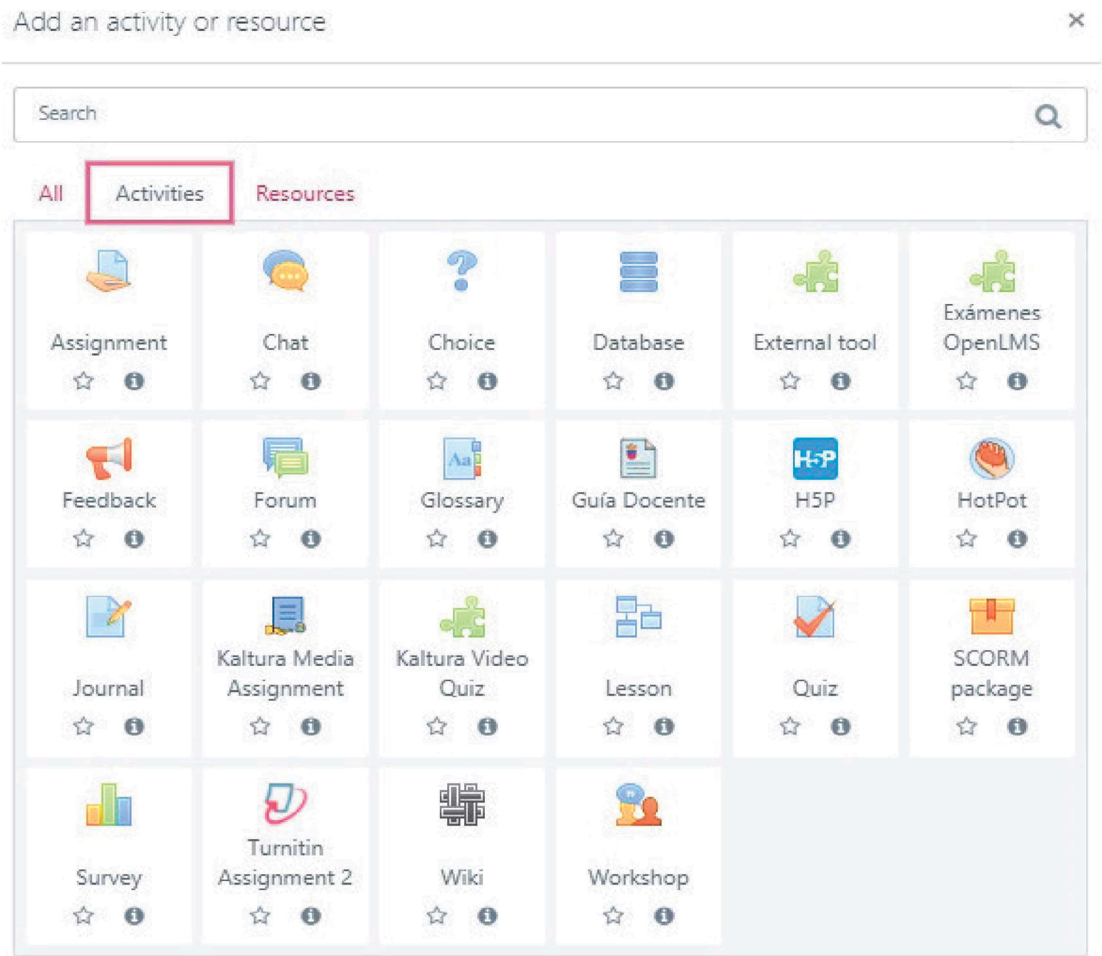

Figure 2. Activities that Moodle v. 3.8 offers on the UBUVirtual platform.

1.1. Form of Teaching and Form of Learning in Blended Learning Environments

As within the modality of presential teaching, the design of the teaching–learning process is, for teachers, essential [10]. The sort of pedagogic design that the teacher implements in Moodle (choice of resources and activities) will have consequences that can affect student motivation and, therefore, student learning. One form of contrasting the effectiveness of a resource or an analysis is a frequency-of-use analysis [14]. This analysis may be carried out in a relatively simple way through the extraction of the records or the logs of the resources and the activities. The extraction can be done in an accessible manner using plugins. They facilitate both the ordering and the extraction of information and specifically, in the Moodle environment, the plugin that Sáiz et al. [15] developed has shown itself to be very effective. This type of tool facilitates the detection of the student at risk of abandonment during the learning process on the LMS [16]. In summary, it implies the confluence of two variables: the teaching style (form of teaching) and the style of learning of the student (form of learning) in the virtual learning environments. Throughout two centuries, many investigations have inquired into the challenge of explaining how learning takes place in presential or Face-to-Face (F2F) teaching sessions. Particularly worth highlighting are the investigative studies on teaching and learning styles and learning strategies within the university environment [17–19]. Nevertheless, there are few studies that have approached the investigation of those aspects in virtual learning environments (e-Learning or Blended Learning), because investigation in this context is still at an early stage [20–22]. With respect to the learning style, the studies of Camarero et al. [18] defined four learning styles in accordance with the classification of Kolb [23]: active style (learning based on direct experience), reflexive style (learning based on observation and data collection), theoretical style (learning based on abstract conceptualization and the preparation of conclusions), and pragmatic style (learning based on active experimentation and the search for practical applications). Likewise, the styles are related to learning strategies, which following the classification of Román and Poggioli [24] may be divided into the strategies of acquisition, codification, recuperation, and metacognitive strategies and support for information processing. Moreover, in accordance with the classification of Veenman [25], the following metacognitive skills may be distinguished: orientation, planning, evaluation, and elaboration. Relating to the styles of teaching and following the studies of Abello et al. [26], it appears that the best structural equations model will be one that includes teacher–student interaction, negotiation over decision-making, the structuring of teaching, and behavioral control.

In summary, the challenge for investigation into instruction within virtual settings is centered on knowing the teaching styles of the teacher and the learning styles of the student [20] and, as a function of those teaching and learning styles, to know which would be the most effective interaction to apply in LMS spaces such as, for example, on Moodle [22]. Active teaching in e-Learning and Blended Learning environments is related to the use and utilization of tools that make possible the construction of the student's own knowledge. To do so, the teacher has to use resources and activities in which oriented process rather than only product feedback is included. Among these tools, we can highlight: (1) orientation towards information (strengthening the use of metacognitive skills for orientation); (2) planning (strengthening the use of metacognitive skills for planning); (3) self-evaluation (strengthening the utilization of self-evaluative metacognitive skills); and (4) self-reflection (strengthening the use of elaborative metacognitive skills) [27]. Likewise, an effective teaching style in these environments appears to be related to: the competences and the teaching experience of the teacher within these environments, the use of evaluation methods that facilitate process-oriented rather than only product-oriented feedback, and the use of hetero-evaluation (self-evaluation and co-evaluation) of both the student and the teacher through the use of the 'Feedback' activity in Moodle [28].

In fact, 6 levels are defined in the European Framework for the Digital competence of Educators (DigCompEdu): A1. Newcomers (have had very little contact with digital tools guidance to expand their repertoire). Explorers (A2) (have started using digital tools, however, without having followed a comprehensive or consistent approach. Explorers need insight and inspiration to expand their competences). Integrators (B1) (use and experiment with digital tools for a range of purposes, trying to understand which digital strategies work best in which contexts). Experts (B2) (use a range of digital tools confidently, creatively, and critically to enhance their professional activities. They continuously expand their repertoire of practices. Leaders (C1) (rely on a broad repertoire of flexible, comprehensive, and effective digital strategies. They are a source of inspiration for others). Pioneers (C2) (question the adequacy of contemporary digital and pedagogical practices, of which they themselves are experts. They lead innovation and are a role model for younger teachers) [29].

1.2. The Digital Society in Higher Education Learning in Both STEM (Science, Technology, Engineering, and Mathematics) and NON-STEM Subject Matter

In this way, therefore, the challenges of both teaching and learning in e-Learning and Blended Learning spaces depends on having professionals and users with digital competencies who can skillfully use the tools on offer in 21st society. In relation to this point, students and teachers from STEM (Science, Technology, Engineering, and Mathematics) academic courses would, in principle, have more competences to approach learning and teaching in Blended Learning environments. Nevertheless, recent investigations have highlighted that if teachers possess digital competences for teaching within these environments, the behavioral patterns of the students in Blended Learning environments are similar in both STEM and non-STEM qualifications [2]. Another aspect to consider is the gender variable. The STEM qualifications attract higher percentages of male students than female students [3,5,7,30–32]. In fact, numerous international projects have been under development over past years to increase the percentage of female students studying STEM qualifications [30–35]. In contrast, the percentage of students studying for Health Sciences and Social Sciences qualifications (for example, Education Science) is inversely related (the percentage of female students is much higher than the percentage of male students). This fact should also be studied to promote parity in these lines of knowledge. It is a reality that is reflected in the data from the CRUE 2017–2018 report [CRUE: Universidades Españolas, a non-profit association formed of a total of 76 Spanish universities (50 public and 26 private), is the main interlocutor on behalf of the universities with the central government and plays a key role in all regulatory developments that affect Higher Education in Spain. http://www.crue.org/] [36], which in turn cites EUROSTAT 2019 as its data source [37]. According to these reports, the average percentage of students who complete STEM qualifications is 28.1% of all qualifications (from least to most ranging from 23.4% in Spain up to 37.5% in Germany). In concrete, in Spain, among the 23.4% of students studying for STEM qualifications, only 26.82% are women. With regard to the qualifications in the branch of Health Sciences, an inverse percentage was found, only 26.2% of all students following these studies are men.

In view of this situation, it might be important to verify whether the gender gap is related to a possible digital divide in the use of technological resources among both teachers and students in virtual teaching environments for STEM vs. Non-STEM qualifications. It should be borne in mind that increasing the digital skills of the general public and social inclusion both figure among the objectives of Agenda 2030 (The 2030 Agenda for Sustainable Development) [4] to achieve quality education [38].

In summary, the road towards equal opportunities starts with quality education that is only achieved through reflection on current practice. Besides, the COVID-19 [1] pandemic has very clearly revealed the digital gaps within education, which have to be overcome to achieve sustainable, quality, and inclusive education [1,38].

The investigation must center on the knowledge of which tools the teacher utilizes within Blended Learning environments in order to respond to the above questions and, by doing so, will be able to define the most effective teaching styles. Likewise, student behavior on the platform must be known in order to define the most effective learning styles [22]. Finally, the possible relations between teaching and learning styles should be studied in virtual settings [39]. It must all be supported through necessary innovation in the form of teaching that implies the use of technological resources [40]. It implies facilitating teaching staff with different instructional methods in virtual environments, so that they use the method that is best suited to their teaching styles and the learning style of their students, to achieve effective and personalized teaching [41,42].

In view of the investigations mentioned earlier, the research questions of this study are as follows:

- RQ1 Will there be significant differences in the use of Moodle resources depending on the expertise of the teacher (e-Learning expert vs. non-expert)?
- RQ2 Will there be significant differences in the frequencies of access to Moodle resources between students studying different subjects depending on the expertise of their teachers (e-Learning expert vs. non-expert)?
- RQ3 Will there be significant differences in the use of Moodle activities depending on the expertise of the teacher (e-Learning expert vs. non-expert)?
- RQ4 Will significant differences be found for the frequency of access to Moodle activities between students as a function of the type of teacher (e-Learning expert vs. non-expert) giving the classes?
- RQ5 Will significant differences be found for the frequency of access to resources among students as a function of the variable gender and the co-variable degree course (STEM vs. Non-STEM) followed?

RQ6 Will significant differences be found for the frequency of access to activities among students as a function of the variable gender and the co-variable degree course (STEM vs. Non-STEM) followed?

RQ7 Will significant differences be found for the frequency of access to Moodle resources among students as a function of the variable gender and the co-variable type of teacher (expert in e-Learning vs. non-expert)?

RQ8 Will significant differences be found for the frequency of access to Moodle activities among students as a function of the variable gender and the co-variable type of teacher (e-Learning expert vs. non-expert)?

2. Materials and Methods

2.1. Participants

Convenience sampling was used following the application of the Fisterra formula [43] for sampling calculation to the population of all possible students at the University of Burgos. From among a total population of 7186 students at a confidence level of 99%, at a precision of 3% and a proportion of 5%, the estimated sampling size was established at 334, with an envisaged proportion of losses of 15%, which pointed to an adjusted sample size of 393 students. In this study, a sample of 626 students (334 women and 292 men) was selected of whom 581 were degree students and 45 were Master's students. Hence, the number of students estimated with the sampling formula was almost doubled. Likewise, the sample was anonymized by a specialist in data coding, in compliance with data protection regulations [Regulation (EU) 2016/679 of the European Parliament and the Council of 27 April 2016)] [44]. The only data that were processed related to information on gender, age intervals (on degree [20–24 years old] and on master's [27–34 years old] courses), and the knowledge branch of the courses. A sample of 13 university teachers was constituted, of whom 11 were female and 2 were men. Among the university teachers, 6 were specialists in e-Learning and Blended Learning teaching environments (all with specialist certificates in "Virtual Teaching" issued by the University of Burgos within the teaching staff training program (https://www.ubu.es/instituto-de-formacion-e-innovacion-educativa-ifie/planes-de-formacion-pdi/plan-de-formacion-para-la-ensenanza-virtual-pfev) and 7 non-specialists in virtual teaching.

The teacher training program in digital competences for Teaching and Learning in Higher Education that is offered at the University of Burgos comprises the following modules: Module 0. 'Transition of Face-to-Face (F2F) teaching to online teaching includes 'Transition towards online teacher' (30 h). Module 1. Technology that comprises 'Technological tools' (68 h), 'Advanced use of the Moodle Platform' (9 h), 'Lesson module on Moodle' (3 h), 'Creation of Virtual Classrooms' (7 h), 'Social networks applied to teaching' (12 h), 'Blogs and microblogging applied to teaching' (12 h), 'Google and Office365 tools for Higher Education' (16 h). Module 2. Content creation that includes 'Creation of educational digital content' (30 h), 'Design of multimedia applications' (20 h), 'Active Presenter applied to teaching' (5 h), 'Collaborative Wikis in Moodle' (2 h), 'Creation of Online Presentations and Courses with Microsoft Office Mix' (5 h). Module 3. Teaching Action that comprises: 'Teaching Action' (142 h), 'eLearning in Online teaching' (30 h), 'Efficient use of tools in online Teaching' (30 h), 'Skills for preparing documents with still and moving images for online teaching' (20 h), 'Tools for manual entries of formulas and their integration in Educational content' (3 h), 'Dynamic communication and interaction in virtual contexts' (16 h), 'iPad as a teaching tool' (3 h), 'Active methodologies in university teaching: project-based learning in Moodle' (32 h), 'Moodle Workshop Module' (8 h). Module 4. This module includes: 'Training design and evaluation (110 h)', 'Design and management of training actions' (30 h), 'eActivities for skills development' (30 h), 'Evaluation in educational online contexts' (30 h), 'Moodle questionnaires' (20 h). The total possible training hours amounted to 742 h. This training plan meets the standards of the European Framework for the Digital Competence of Educators (DigCompEdu) https://ec.europa.eu/jrc/sites/jrcsh/files/digcompedu_leaflet_en-2017-11-14.pdf.

It is, therefore, considered that teachers who have received this training are experts in eLearning and are ranked at level C1 (Leaders) of the European Framework, while the teachers who are considered as non-experts are ranked at levelA2 (Explorers) [29].

The teachers also imparted courses related both to STEM (Engineering) and to non-STEM (Science and Health Education) subjects on 9 degrees in presential classes, 1 on-line (non-presential degree), 1 Master's course in presential classes, and 2 Blended Learning Master's course, involving a total of 13 study units. All participants collaborated on a voluntary basis, having previously given their informed consent in writing and without having received any economic incentive (see Table 1). The average percentages of male and female students on STEM academic courses were 84.16% and 15.84%, respectively. In relation to the Non-STEM degree courses, the percentages of male and female students were 9.20% and 90.80%, respectively; and in Education Science, 7.77% and 92.23%, respectively. Work proceeded with an initial sample of 626 students, although the sample lost 12 students throughout the process.

Table 1. Sample characteristics.

Degree Type	Subject Type	Teacher Type	*n* (Students)	Students Gender			
				Men	%	Women	%
Degree (F2F)	STEM	2	90	80	88.89	10	11.11
Degree (F2F)	Non-STEM (Education Science)	1	38	1	2.63	37	97.37
Degree (F2F)	STEM	2	116	108	93.10	8	6.90
Degree (e-Learning)	STEM	2	27	20	74.07	7	25.93
Master (Blended Learning)	Non-STEM (Health Sciences)	1	15	1	6.67	14	93.33
Degree (F2F)	Non-STEM (Health Sciences)	2	52	7	13.46	45	86.54
Degree (F2F)	Non-STEM (Education Science)	1	77	13	16.88	64	83.12
Degree (F2F)	Non-STEM (Education Science)	2	13	1	7.69	12	92.31
Master (F2F)	Non-STEM (Education Science)	1	15	1	6.67	14	93.33
Master (Blended Learning)	Non-STEM (Health Sciences)	2	15	1	6.67	14	93.33
Degree (F2F)	STEM	1	36	29	80.56	7	19.44
Degree (F2F)	Non-STEM (Health Sciences)	1	60	6	10.00	54	90.00
Degree (F2F)	Non-STEM (Education Science)	1	60	3	5.00	57	95.00

Note: Type of teacher: 1 = non-specialist teachers in Blended Learning environment; 2 = specialist teachers in Blended Learning environments; F2F = teaching face-to-face.

2.2. Instruments

(a) UBUVirtual Platform. This platform is an LMS developed in the Moodle environment, version 3.8. All the resources and activities that Moodle has to offer were studied (see Tables A1 and A2).

(b) "eOrientation" Moodle Plugin. This plugin was developed within an ongoing research project funded by the Junta de Castilla y León (Spain). The plugin can be used to set up customized access to the course (subject) modules that are available on each course. Likewise, personalized notifications related to learning process monitoring can be sent to a student or a group of students using the plugin through emails sent via a platform-messaging system. In addition, a table with all or part of the information that is registered can be exported in different formats (.csv, .xlsx, HTML table, .json, .ods, .pdf). More detailed information on the "eOrientation" plugin is presented in the development of objective 1 (see point 6: Patents) in the results section [15,45].

2.3. Statistical Analysis

A $2 \times 2 \times 2$ factorial design (type of teacher, type of degree, gender) was applied. A non-parametric statistical test (Mann–Whitney U-test for independent samples) was used to test research questions RQ1 and RQ3, as work was done with 13 teachers. ANOVA tests were used to test RQ2 and RQ4 and the eta-squared effect value. Likewise, ANCOVAs were used to test the eta-squared effect value. These analyses were completed with statistical software package SPSS v.24. [46].

2.4. Procedure

The authorization of the Bio-Ethics Committee of the University of Burgos was successfully requested. Likewise, as indicated under point 2.1, participation was voluntary with informed consent provided in writing and without any financial incentives. The study took place during the first semester (six months) of the 2019/20 academic year. At the end of the semester, the Moodle logs of the 13 study units were extracted. Subsequently, the Moodle plugin "eOrientation" [41] that, as pointed out under 2.2, is used to arrange the logs in a comprehensible manner, was used to study the resources and activities that the participating teachers had selected. In Table A2, the resources and activities that may be used on Moodle are presented and those used for each subject are noted. Finally, the statistical analyses described in Section 2.4 were applied.

3. Results

A non-parametric statistical test, the Mann–Whitney U-test for independent samples [type of teacher (expert in e-Learning vs. non-expert)], was applied to test RQ1, as it involves a sample of n = 13 teachers. Significant differences were found for the use of resources, specifically those of 'Label' and 'Page' (see Table 2). The teachers used 5 resources of the 8 that Moodle v.3.8 has to offer, which implies a percentage utilization of 62.5%, without there being a difference in the variable type of teacher (expert in e-Learning vs. non-expert). The resources used as a function of this variable may be consulted in Figures 3 and 4.

Table 2. Mann–Whitney U-test for independent samples (type of teacher: non-expert teachers in e-Learning vs. expert teachers) with respect to the utilization of Moodle resources.

Resource	Mean Rank		Mann–Whitney U-Test	p
	G1	G2		
	n = 7	n = 6		
File	7.50	6.42	17.50	0.28
Folder	5.71	8.50	12.00	0.80
Label	5.29	9.00	9.00	0.03 *
Page	4.43	10.00	3.00	0.003 *
URL	7.07	6.92	20.50	0.95

* $p < 0.05$. Note: G1 = non-expert teacher in e-Learning; G2 = expert teacher in e-Learning.

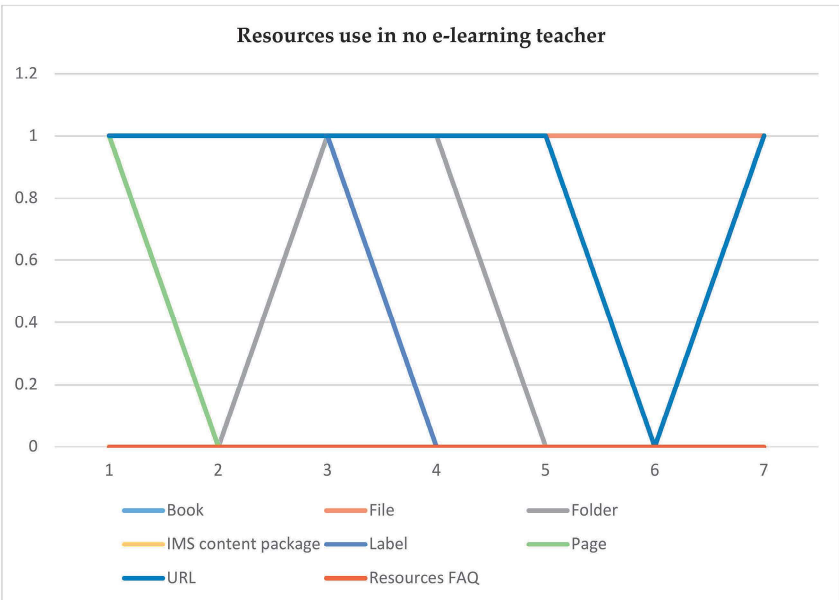

Figure 3. Use of resources: non e-learning teachers.

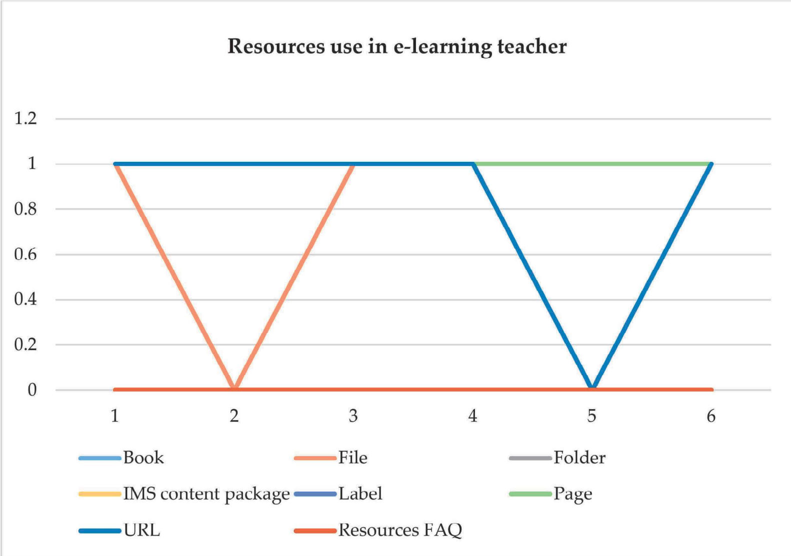

Figure 4. Use of resources: e-learning teachers.

Subsequently, a fixed-effects ANOVA type of teacher (expert in e-Learning vs. non-expert teacher) was applied to test RQ2. Significant differences were found between students for the frequency of utilization of 'Folder', 'Page', and 'URL' resources. The students belonging to the groups with expert e-learning teachers made greater use of the 'Page' and the 'URL' resources (see Table 3).

Table 3. Single fixed-effects ANOVA (type of teacher: non-expert teachers in e-Learning vs. expert teachers) for Moodle resources used.

	N	G1		G2		df	F	p	η^2
		n	M (SD)	n	M (SD)				
File	625	308	70.55 (51.54)	317	77.82 (52.85)	(1,623)	3.03	0.08	0.01
Folder	510	193	12.80 (20.63)	317	5.84 (19.57)	(1,508)	14.58	0.00 *	0.03
Label	446	129	0.56 (3.98)	317	2.83 (13.22)	(1,444)	3.68	0.56	0.01
Page	355	38	0.03 (0.16)	317	11.05 (16.70)	(1,353)	16.52	0.00 *	0.05
URL	521	189	2.01 (5.96)	332	14.92 (25.07)	(1,519)	48.54	0.00 *	0.09

* $p < 0.05$. Note: G1 = non-specialist e-learning teacher; G2 = specialist e-Learning teacher; M = Mean; SD = Standard Deviation; df = degrees of freedom, η^2 = eta squared effect value.

The Mann–Whitney U-test for independent samples was applied to test RQ3. No significant differences were found for the utilization of activities to which both types of teachers had access on Moodle ('Assignment', 'Feedback', 'Forum', 'Glossary', 'Quiz'), only a tendency towards a difference in the utilization of the 'Quiz' activity (see Table 4). In addition, the teachers utilized 66.66% of the activities available on Moodle v.3.8. In this case, differences were detected for the percentages of use of the range of activities. The non-expert and the expert e-Learning teachers, respectively, utilized the learning objects at levels of 33.33% and 66.66%, respectively (see Figures 5 and 6).

An ANOVA (type of teacher: expert in e-Learning vs. non-expert teacher) was applied (see Table 5) to test RQ4. Significant differences were found for the use of Moodle activities among the students, depending on the variable type of teacher. Average use was higher among the group of students with an expert e-Learning teacher.

Table 4. Mann–Whitney U-test for independent samples (type of teacher: non-expert vs. expert in e-Learning) with respect to the utilization of Moodle activities.

Moodle Activities	Mean Rank G1 $n = 7$	Mean Rank G2 $n = 6$	Mann–Whitney U-Test	p
Assignment	7.00	7.00	21.00	1.00
Feedback	5.86	8.33	13.00	0.19
Forum	7.00	7.00	21.00	1.00
Glossary	6.00	8.17	14.00	0.11
Quiz	5.43	8.83	10.00	0.06

* $p < 0.05$. Note: G1 = non-expert e-Learning teacher; G2 = expert e-Learning teacher.

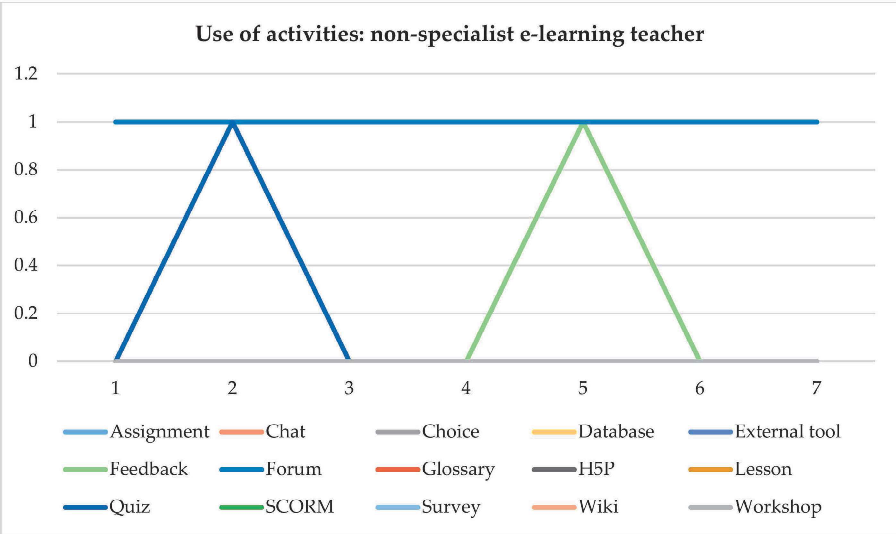

Figure 5. Frequency of use of Moodle resources among non-specialist e-Learning teachers.

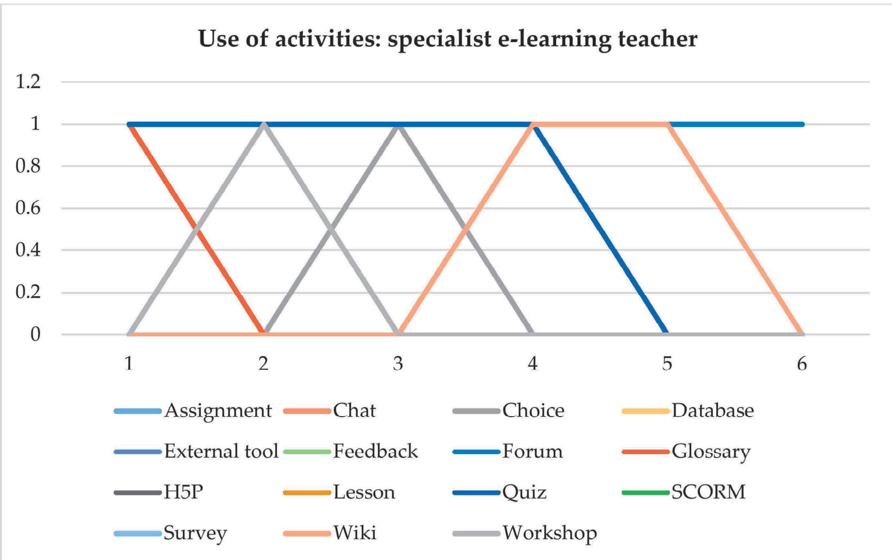

Figure 6. Frequency of use of Moodle resources among specialist e-Learning teachers.

Table 5. Single fixed-effects ANOVA (type of teacher expert vs. non-expert in e-Learning) for activities utilized on Moodle.

Activities on Moodle	N	G1		G2		df	F	p	η^2
		n	M (SD)	n	M (SD)				
Assignment	603	296	59.40 (119.82)	307	168.83 (179.76)	(1,602)	56.71	0.000 *	0.09
Feedback	364	60	0.27 (0.52)	304	7.80 (19.70)	(1,362)	8.76	0.003 *	0.02
Forum	564	232	2.16 (8.79)	332	21.38 (48.97)	(1,562)	34.93	0.00 *	0.06
Quiz	320	18	47.94 (36.07)	302	99.39 (166.24)	(1,318)	1.71	0.19	0.01

* $p < 0.05$. Note: G1 = non-specialist e-Learning teacher; G2 = specialist e-Learning teacher; M = Mean; SD = Standard Deviation; df = degrees of freedom, η^2 = eta squared effect value.

The activities used by the teachers for the different study units may be consulted in Table A3.

RQ5 was tested with a single fixed-effects ANCOVA (student gender and co-variable type of degree, STEM vs. Non-STEM). No significant differences were found, neither for the utilization of resources, nor for the gender variable, nor for the covariable type of degree. Nevertheless, the effect values of both the variable and the covariable were high for the 'Folder' resource (see Table 6).

Table 6. Single fixed-effects ANCOVA results for the dependent variable student gender and co-variable type of degree (STEM (Science, Technology, Engineering, and Mathematics) vs. Non-STEM) in relation to the independent variable 'frequency of use of Moodle resources'.

		N	G1		G2		df	F	p	η^2
			n	M (SD)	n	M (SD)				
Independent Variable	File	626	334	74.14 (54.76)	292	74.09 (49.51)	(1,1)	0.07	0.83	0.07
	Folder	511	273	11.14 (18.60)	238	5.38 (21.57)	(1,1)	5.24	0.26	0.84
	Label	447	199	2.89 (11.58)	248	1.59 (11.20)	(1,1)	0.04	0.88	0.04
	Page	356	135	8.93 (11.61)	221	10.41 (18.36)	(1,1)	0.52	0.60	0.35
	URL	522	237	12.32 (27.45)	285	8.46 (13.93)	(1,1)	0.40	0.64	0.28
Co-variable Type of Degree	File						(1,1)	0.01	0.93	0.01
	Folder						(1,1)	16.57	0.15	0.94
	Label						(1,1)	0.20	0.73	0.17
	Page						(1,1)	0.06	0.84	0.06
	URL						(1,1)	2.02	0.39	0.67

* $p < 0.05$. Note: G1 = female student gender; G2 = male student gender; M = Mean; SD = Standard Deviation; df = degrees of freedom, η^2 = eta squared effect value.

Subsequently, a single-factor fixed-effects ANCOVA was applied to test RQ6, in relation to student gender and type of degree (STEM vs. Non-STEM) and the dependent variable 'use of Moodle activities'. Significant differences were found with regard to the independent variable gender for the use of 'Assignment' activities ($p = 0.009$) and an effect of the covariable type of degree was found for the 'Glossary' activity ($p = 0.007$) (see Table 7).

A single-factor fixed-effects ANCOVA was applied to test RQ7 for the dependent variables student gender and expertise of teacher (expert in e-Learning vs. non-expert) in relation to the dependent variable 'Use of Moodle resources'. Neither significant differences nor a large effect size was found for the covariable except in 'Page' and 'URL' (see Table 8).

Table 7. Single-factor fixed-effects ANCOVA results for the dependent variable student gender and the co-variable type of degree (STEM vs. Non-STEM) in relation to the independent variable 'frequency of use of Moodle activities'.

		N	G1		G2		df	F	*p*	η^2
			n	M (SD)	*n*	M (SD)				
Independent Variable	Assignment	604	321	83.67 (132.27)	283	150.36 (185.21)	(1,1)	4932.19	0.009 *	0.99
	Feedback	364	139	13.75 (27.17)	225	2.12 (5.56)	(1,1)	2.21	0.38	0.69
	Forum	564	284	8.77 (26.07)	280	18.25 (48.53)	(1,1)	1.05	0.49	0.51
	Glossary	87	61	3.13 (3.93)	26	0.88 (2.25)	(1,1)	5.09	0.27	0.84
	Quiz	320	84	83.76 (154.16)	236	101.03 (164.96)	(1,1)	1.16	0.48	0.54
Co-variable Type of Degree	Assignment						(1,1)	118.03	0.06	0.99
	Feedback						(1,1)	1.87	0.40	0.65
	Forum						(1,1)	0.59	0.58	0.37
	Glossary						(1,1)	8070.72	0.007 *	0.99
	Quiz						(1,1)	9.78	0.20	0.91

* $p < 0.05$. Note: G1 = students gender female; G2 = students gender male; M = Mean; SD = Standard Deviation; df = degrees of freedom, η^2 = eta squared effect value.

Table 8. Single-factor fixed-effects ANCOVA for the dependent variable student gender and the co-variable expertise of teacher (expert in e-Learning vs. non-expert) in relation to the independent variable 'frequency of use of Moodle resources'.

		N	G1		G2		df	F	*p*	η^2
			n	M (SD)	*n*	M (SD)				
Independent Variable	File	625	333	74.36 (54.69)	292	74.09 (49.51)	(1,1)	0.27	0.69	0.21
	Folder	510	272	11.18 (18.62)	238	5.38 (21.57)	(1,1)	1.44	0.44	0.59
	Label	446	198	2.91 (11.60)	248	1.59 (11.20)	(1,1)	0.32	0.67	0.24
	Page	355	134	8.99 (11.62)	221	10.41 (18.36)	(1,1)	1.06	0.49	0.51
	URL	521	236	12.38 (27.49)	285	8.46 (13.93)	(1,1)	1.02	0.50	0.51
Co-variable Expertise of Teacher	File						(1,1)	1.32	0.46	0.57
	Folder						(1,1)	0.28	0.69	0.22
	Label						(1,1)	1.15	0.48	0.53
	Page						(1,1)	139.93	0.05	0.99
	URL						(1,1)	4.98	0.27	0.83

* $p < 0.05$. Note: G1 = students gender female; G2 = students gender male; M = Mean; SD = Standard Deviation; df = degrees of freedom, η^2 = eta squared effect value.

Finally, a single-factor fixed-effects ANCOVA was applied to test RQ8 for the dependent variables student gender and expertise of teacher (expert in e-Learning vs. non-expert) in relation to the dependent variable 'Use of Moodle activities'. No significant differences were found with regard to the independent variable student gender, although the effect-sizes of the activities 'Forum', 'Glossary', and 'Quiz' were high. Likewise, an effect was found for the covariable expertise of teacher on the Forum activity ($p = 0.04$) and high effect-size values were found for the activities 'Forum', 'Glossary' ($p = 0.007$), and 'Quiz' ($p = 0.09$) (see Table 9).

Table 9. Single fixed-effects ANCOVA applied to test RQ8 for the dependent variable student gender and co-variable type of teacher (e-Learning expert vs. non-expert) in relation to the independent variable 'Frequency of use of Moodle activities'.

		N	G1		G2		df	F	*p*	η^2
			n	M (SD)	*n*	M (SD)				
Independent Variable	Assignment	603	320	83.93 (132.39)	283	150.36 (185.21)	(1,1)	0.07	0.84	0.06
	Feedback	364	139	13.75 (27.17)	225	2.12 (5.56)	(1,1)	1.06	0.49	0.52
	Forum	564	284	8.77 (26.07)	280	18.25 (48.53)	(1,1)	3.83	0.30	0.79
	Glossary	87	61	3.13 (3.93)	26	0.88 (2.25)	(1,1)	5.09	0.27	0.84
	Quiz	320	84	83.76 (154.15)	236	101.03 (164.96)	(1,1)	10.89	0.19	0.92
Co-variable Type of Degree	Assignment						(1,1)	4.55	0.28	0.82
	Feedback						(1,1)	1.49	0.44	0.60
	Forum						(1,1)	200.23	0.04 *	0.99
	Glossary						(1,1)	8070.72	0.007 *	0.99
	Quiz						(1,1)	51.91	0.09 *	0.98

* $p < 0.05$. Note: G1 = students gender female; G2 = students gender male; M = Mean; SD = Standard Deviation; df = degrees of freedom, η^2 = eta squared effect value.

4. Discussion

We begin with a significant data item, which is that the average percentage of male students following STEM qualifications was 84.16% and 15.84% were female students. The same percentages both for Non-STEM Health Sciences and for Education Science qualifications were 9.20% and 90.80% followed by 7.77% and 92.23%, respectively. This fact initially supported the existence of a gender divide on STEM vs. Non-STEM courses, in the former towards a higher presence of female students and in the second towards a higher presence of male students [3,5,7,30–35].

In addition, it has been found that the utilization of Moodle resources differed depending on whether the teacher was an expert in e-Learning vs. a non-expert regardless of the teaching modality (F2F, Blended Learning, or e-Learning). In particular, the expert teachers used more resources with their students linked to the implementation of metacognitive skills for planning, such as 'Label' (a resource that facilitates the cognitive structuring of information) and 'Page' (a resource that facilitates the embedding of videos) [22,27,28]. Even so, it must be pointed out that the expert teachers only utilized 62.5% of possible resources, which indicates that this type of teacher could still increase the inclusion of other resources and activities that enrich teaching in virtual spaces such as 'IMS content package' and 'Resources FAQ'. Likewise, greater homogeneity was found for the resource type and for the frequency of use in the group of expert e-Learning teachers, which indicates that resources were used in the group of the non-experts, though with neither the same frequency nor uniformity. With regard to the use of the Moodle-related activities in teaching, an important difference was found between the number of activities utilized as a function of the variable type of teacher. The expert e-Learning teachers utilized 66.55% of all possible activities and the non-expert teachers only used 33.33%. In addition, within the activities in which both types of teachers coincided over the use ('Assignment', 'Feedback', 'Forum', 'Glossary', 'Quiz'), the expert e-Learning teachers utilized the 'Feedback' resources that facilitate the use of self-evaluation and evaluation on the platform, as well as a higher frequency of use of the 'Forum'. Likewise, in this case, greater homogeneity between the expert e-Learning teachers was found, in opposition to less uniformity among the non-expert teachers. The expert e-Learning teacher, moreover, utilized more Moodle resources and activities that may be related to the strengthening of all the metacognitive skills among the students. In contrast, the non-expert teachers fundamentally utilized activities related to orientation and planning skills [22,27,28]. These teachers probably compensate the presential activities with the use of the other skills. However, the aim of this study was to analyze the use of the platform and how it occurs from the perspective of a teaching system increasingly conducted in non-F2F classrooms. Nevertheless, the expert teachers only utilized 66.66% of all possible activities, others such as 'Chat', 'Choice', 'Database', 'Lesson', 'Survey', 'Wiki', and 'Workshop' were not utilized in a homogenous way and their frequency of use was low.

Likewise, it was confirmed that the teaching style appears to condition student behavior on the LMS, which supports what has been found in other investigations [1,2,8–12]. This aspect sheds light on the frequency of use of resources and activities, suggesting that it depends on the instructional design that the teacher implements. It is of relevance to the study of the pedagogic designs within the LMS that activate the options that these environments have to offer.

Nevertheless, the results of this study have to be treated with prudence as the work over one academic year involved teachers and students from a single university and with a limited number of qualifications. In future investigations, therefore, the number of universities and qualifications in the sample will be enlarged and the timeline of the study extended.

5. Conclusions

In the knowledge society of the 21st century, the use of technological teaching tools is very necessary. This necessity has been accentuated by the COVID-19 health crisis that is affecting humanity. The results that have been found in this study coincide with warnings from international bodies over the past few years. It relates to the existence of a gender gap and a digital divide [3–5,7,36–38]. The gender differences found in this study relating to the use of Moodle resources and activities among students and teachers may, in part, be explained by a higher number of expert e-Learning teachers on STEM degrees. This fact is understandable because these qualifications have traditionally contained technologies that have facilitated teacher training. In addition, as previously indicated, the percentage of male students on STEM qualifications is significatively higher, which can explain the gender differences that have been found. It is, therefore, quite clear that there is an urgent need for teachers and students to be trained to utilize the tools that LMS has to offer [26–28], so as to mitigate the gender gap found as a function of the type of STEM v. Non-STEM qualification [30–35]. Along the same lines, the expert e-Learning professors utilized more resources and activities from among all of Moodle's possibilities, although not all of them employ those resources and activities with the same frequency. It follows that their use should be facilitated by providing training and support to the teaching staff because the development of any of those tools in the LMS entails a lot of time and dedication. This aspect is important because it is related to a previously detected need that the European Commission has underlined, related to the importance of taking into account the digital competences of teachers. These competences should be evaluated against the standards of the European Framework for the Digital Competence of Educators (DigCompEdu) [29]. However, if government organs and educational institutions are to do so, procedures need to be in place to evaluate digital training at the 6 levels of competence that the European Commission has established to achieve equal standards for the evaluation of digital skills.

These aspects are important points upon which university managers might do well to reflect, with the objective of trying to find responses that can mitigate these effects and increase the utilization and the frequency of use of the tools that the LMS has to offer and so that their utilization is neither related with the type of teacher, nor with the type of qualification that, as has been seen, is related with gender. It will all mean that students can be offered the same opportunities for on-line teaching that is up to date and effective. It is, therefore, important to underline that both aspects are objectives of Agenda 2030 [4] attempting to achieve inclusive quality education that reduces the effects of the gender gap and the digital divide [36].

Finally, it may be highlighted that future research works will approach the study of student motivations behind the choice of STEM vs. Non-STEM degrees. In addition, the question will be analyzed of whether teaching on STEM vs. NON-STEM degrees and the teaching modality (F2F vs. e-Learning) are related to certain didactic designs. Likewise, whether the digital competences of the students can influence these teaching processes will also be studied. Along these lines, it would be recommendable for the governance bodies of universities to consider the need to design training courses on digital competences, to alleviate the possible gender gap on degree courses that have no study modules with these curricular contents as part of their curricular content.

6. Patents

Sáiz-Manzanares, M.C.; Marticorena-Sánchez, R.; Escolar-Llamazares, M.C. eOrientation Computer Software for Moodle. Detection of the student at academic risk at University; 00/2020/588; General Registry of Intellectual Property: Madrid, Spain, 16 January 2020 [45].

Author Contributions: Conceptualization, M.C.S.-M. and R.M.-S.; methodology, M.C.S.-M.; software, M.C.S.-M., R.M.-S., M.-C.E.-L. and S.R.-A.; validation, M.C.S.-M., R.M.-S., N.M.-R., S.R.-A., M.-C.E.-L., N.A.-S., M.Á.M.-M. and E.I.M.-V.; formal analysis, M.C.S.-M.; investigation, M.C.S.-M., R.M.-S., N.M.-R., S.R.-A., M.-C.E.-L., N.A.-S., M.Á.M.-M. and E.I.M.-V.; resources, M.C.S.-M., R.M.-S., N.M.-R., S.R.-A., M.-C.E.-L., N.A.-S., M.Á.M.-M. and E.I.M.-V.; data curation, M.C.S.-M.; writing—original draft preparation, M.C.S.-M., N.M.-R. and S.R.-A.; writing—review and editing, M.C.S.-M., R.M.-S., N.M.-R., S.R.-A., M.-C.E.-L., N.A.-S., M.Á.M.-M., and E.I.M.-V.; visualization, M.C.S.-M.; supervision, M.C.S.-M., R.M.-S., N.M.-R., S.R.-A., M.-C.E.-L., N.A.-S., M.Á.M.-M. and E.I.M.-V.; project administration, M.C.S.-M., N.M.-R., S.R.-A., M.-C.E.-L., N.A.-S., M.Á.M.-M. and E.I.M.-V.; funding acquisition, M.C.S.-M., N.M.-R., S.R.-A., M.-C.E.-L., N.A.-S., M.Á.M.-M. and E.I.M.-V. All authors have read and agreed to the published version of the manuscript.

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Institutional Review Board Statement: The Ethics Committee of the University of Burgos approved this study, Nº IR 30/2019 11 of November of 2019.

Informed Consent Statement: 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.

Data Availability Statement: Not applicable.

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Conflicts of Interest: The authors declare no conflict of interest.

Ethics Statement: The Ethics Committee of the University of Burgos approved this study, Nº 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.

Appendix A

Table A1. Moodle resources and relations with the metacognitive skills following Veenman classification [25].

Resources	Definition	Relation with Metacognitive Skills Following the Classification of Veenman [20]
Book	Creates multi-page resources with a similar format to a book.	Orientation Metacognitive skills
File	Opens a file that can include support files; for example, an HTML page with embedded images and Flash objects.	Orientation Metacognitive skills
Folder	Displays a group of related files within a single folder.	Orientation Metacognitive skills
IMS content package	IMS is a body that helps define technical standards for various actions, including material for e-learning. The IMS content package specification makes it possible for materials to be stored in a standard format, which can be reused in different systems, without the need to convert the material into new formats.	Orientation Metacognitive skills

Table A1. *Cont.*

Resources	Definition	Relation with Metacognitive Skills Following the Classification of Veenman [20]
Label	The tag module permits the insertion of text and multimedia elements on the course pages between the links to other resources and activities. This module facilitates the orientation of the student towards the contents and resources of the subject and therefore the cognitive structuring of the information.	Orientation and Planning Metacognitive skills
Page	This resource is more accessible and easily updateable than the file resource. It also facilitates the embedding of videos.	Orientation and Planning Metacognitive skills
URL	It includes Internet links as a course resource (documents or images, videos, etc.) and an URL option as embedded or open in a new window. URLs can also be added to other resources or activities through the text editor.	Orientation and Planning Metacognitive skills
FAQ	A very common tool in all types of online communities that are used to save time looking for help.	Orientation Metacognitive skills
Activities		
Assignment	With this module, the teacher can evaluate the learning of their students and give process or product-oriented feedback on the learning response. Students can present any digital content, such as text documents, spreadsheets, images, audio, and videos among others.	Evaluation and Elaboration Metacognitive skills
Chat	Chat can be a one-off activity or it can be repeated at the same time every day or every week. Chat sessions are saved and can be made public for all to see or can be limited to users with permission. The chats are especially useful when a group has no opportunity to meet up physically for F2F conversations and the sharing of experiences with other classmates from the same course but from different cities or countries.	Orientation and Planning Metacognitive skills
Choice	The module allows the teacher to ask a question specifying the possible answers. The results of the election can be published immediately after the consultation, on a certain date, or not published. This tool can be used to take a quick survey to check student understanding of a specific topic. All of the above help the teacher when making decisions.	Orientation and Planning Metacognitive skills
Database	Participants can create, maintain, and search for information in a repository of records. The teacher defines the structure of the entries according to a list of fields. Database activities have many uses, such as a collection of collaborative web links, books, book reviews, journal references, among others.	Orientation Metacognitive skills
External tool	Participants can interact with resources and learning activities that comply with data protection and intellectual property regulations.	Orientation and Planning Metacognitive skills
Feedback	The teacher can create customized surveys to obtain participant feedback on a variety of question types: multiple choice, yes/no, or open-ended. Survey responses can be anonymous. Likewise, the results can be shown to all participants or only to teachers.	Evaluation and Elaboration Metacognitive skills

Table A1. *Cont.*

Resources	Definition	Relation with Metacognitive Skills Following the Classification of Veenman [20]
Forum	Participants can have asynchronous discussions and the Forums can be of different types. The teacher can give permissions for files to be attached to forum posts. Forum posts can be graded by teachers or students (peer review) and ratings can be added to a final grade that is recorded in the gradebook.	Orientation and Planning Metacognitive skills
Glossary	The teacher can define the key concepts of the subject in the Glossary. Likewise, the teacher can give permissions to students to include partial definitions of a concept and can supervise their content before they are entered. Entries can be searched and browsed alphabetically or by category, date, or author. This is a very useful resource for student learning.	Orientation and Planning Metacognitive skills
H5P	H5P is an abbreviation for HTML5 Package. The teacher can create content with it, such as: interactive videos, exams, and presentations. H5P activities can be created, edited, and added to Moodle.	Orientation and Planning Metacognitive skills
Lesson	The teacher can use this module to present content and/or practical activities in an interesting and flexible way. Lesson can be used to create a linear set of content pages and educational activities that offer the student various pathways or options. In either case, teachers can choose to increase student engagement and aid understanding by including different types of questions, such as multiple-choice, short answer, and matching answer. Depending on the answer chosen by the student and how the teacher develops the lesson, students can go to the next page, go back to a previous page, or follow a totally different itinerary. A lesson can be graded in the gradebook.	Orientation, planning, and elaboration Metacognitive skills
Quiz	The teacher can design and post questionnaires with multiple-choice, true/false, coincidence, short answer, and numerical answer questions. The teacher can limit the completion of the questionnaire to multiple attempts, with the questions ordered or randomly selected from the question bank. A time limit can be set. Each attempt is automatically graded, and the result is saved in the gradebook. The teacher can determine if and when the results, feedback comments, and correct and incorrect answers are displayed to the student and the reasons and where the solution and explanation can be found in the subject materials.	Evaluation and Elaboration Metacognitive skills
SCORM	A set of files that are packaged according to a standard rule for learning objects. Using the SCORM activity module, SCORM or AICC packages can be uploaded and added to course material as zip files. SCORM activities can be used for the presentation of multimedia content and animations.	Orientation and Planning Metacognitive skills

Table A1. *Cont.*

Resources	Definition	Relation with Metacognitive Skills Following the Classification of Veenman [20]
Survey	This tool provides a number of verified survey instruments, including COLLES (Constructivist Online Learning Environment Survey) and ATTLS (Attitudes Toward Thinking and Learning Survey), which have been found useful in assessing and stimulating learning in online environments. Teachers can use them to gather data to help them reflect on their own practice.	Evaluation and Elaboration Metacognitive skills
Wiki	A collaborative participative environment that is basically a web page that all the participants of a class can create together from the Internet browser, with no prior knowledge of HTML.	Orientation, Planning, Evaluation, and Elaboration Metacognitive skills
Workshop	The workshop activity module connects collections, reviews, and peer evaluations of student work. Students can submit any digital content (files), such as a word processor or spreadsheet documents, and can also type the text directly into a field using a text editor (within Moodle). Submissions are evaluated using a teacher-defined multi-criteria evaluation format. Students will have two grades for the workshop activity: one grade for submitting it and one for peer review. Both grades are saved in the gradebook.	Orientation, Planning, evaluation, and elaboration Metacognitive skills

Table A2. Resources utilized by the teachers for the different academic courses.

Subject	Teacher Type	Study Type	Resources							
			Book	File	Folder	IMS Content Package	Label	Page	URL	Resources FAQ
1	2	Degree (F2F)	-	X	X	-	X	X	X	-
2	1	Degree (F2F)	-	X	X	-	X	X	X	-
3	2	Degree (F2F)	-		X	-	X	X	X	-
4	2	Degree (e-Learning)	-	X	X	-	X	X	X	-
5	1	Master (Blended Learning)	-	X	-	-	X		X	-
6	2	Degree (F2F)	-	X	X	-	X	X	X	-
7	1	Degree (F2F)	-	X	X	-	X		X	-
8	2	Degree (F2F)	-	X	X	-	X	X		-
9	1	Master (F2F)	-	X	X	-			X	-
10	2	Master (Blended Learning)	-	X	X	-	X	X	X	-
11	1	Degree (F2F)	-	X	-	-			X	-
12	1	Degree (F2F)	-	X	-	-				-
13	1	Degree (F2F)	-	X	X	-			X	-

Table A3. Activities utilized by the teachers on the different academic courses.

Subject	Teacher Type	Study Type	Activities														
			Assignment	**Chat**	**Choice**	**Database**	**External tool**	**Feedback**	**Forum**	**Glossary**	**H5P**	**Lesson**	**Quiz**	**SCORM**	**Survey**	**Wiki**	**Workshop**
1	2	Degree (F2F)	X	X	X	-	-	X	X	X	-	-	X	-	-	-	-
2	1	Degree (F2F)	X	-	-	-	-		X	-	-	-		-	-	-	-
3	2	Degree (F2F)	X		-	-	-	X	X	-	-	X	X	-	-	-	X
4	2	Degree (e-Learning)	X	X	X	-	-	X	X	-	-	-	X	-	-	-	-
5	1	Master (Blended Learning)	X	-	-	-	-		X	-	-	-	X	-	-	-	-
6	2	Degree (F2F)	X	-	-	-	-	X	X	X	-	-	X	-	-	X	-
7	1	Degree (F2F)	X	-	-	-	-	-	X	-	-	-	-	-	-	-	-
8	2	Degree (F2F)	X	-	-	-	-	-	X	-	-	-	-	-	-	X	-
9	1	Master (F2F)	X	-	-	-	-	-	X	-	-	-	-	-	-	-	-
10	2	Master (Blended Learning)	X	-	-	-	-	-	X	-	-	-	-	-	-	-	-
11	1	Degree (F2F)	X	-	-	-	-	X	X	-	-	-	-	-	-	-	-
12	1	Degree (F2F)	X	-	-	-	-	X	X	-	-	-	-	-	-	-	-
13	1	Degree (F2F)	X	-	-	-	-		X	-	-	-	-	-	-	-	-

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Figura 3.5: JIF Revista *Sustainability*. Fuente: WOS (31/07/2021)

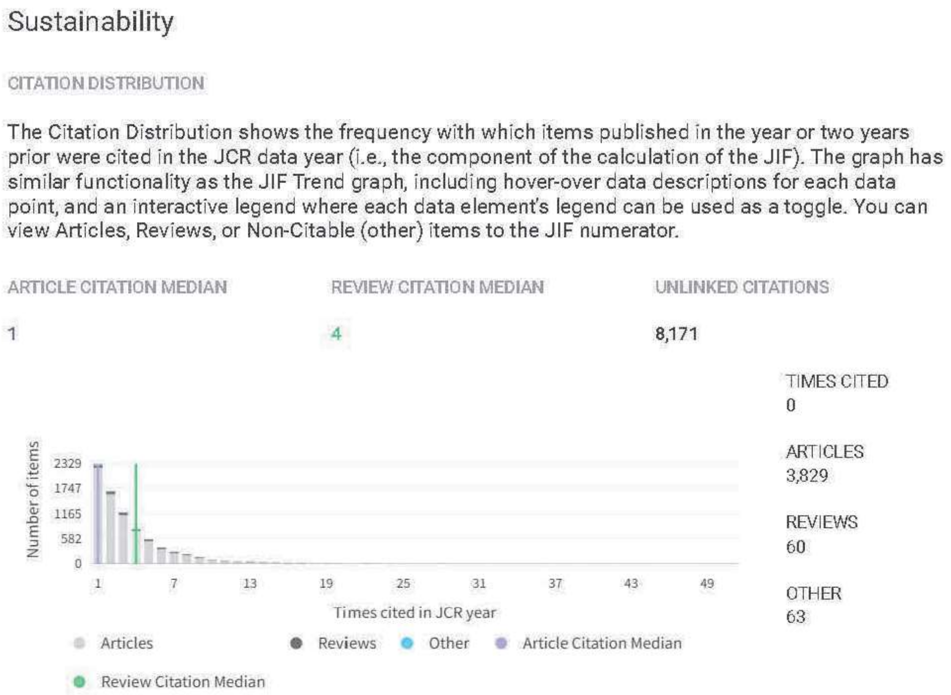

Figura 3.6: Citaciones Revista *Sustainability*. Fuente: WOS (31/07/2021)

3.1.2.2. Estándares de calidad del artículo 2

Esta aportación tiene 1 citación y 43 referencias en la *Web of Science* como puede verse en la imagen 3.7. En los registros de las métricas de la revista desde la fecha de su publicación 22 de enero de 2021 el artículo ha tenido 937 visitas y ha sido descargado más de 800 veces y ha registrado 4 citas (ver imagen 3.8).

3.1.3. Artículo 3: *Monitoring of Student Learning in Learning Management Systems: An Application of Educational Data Mining Techniques*

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Article

Monitoring of Student Learning in Learning Management Systems: An Application of Educational Data Mining Techniques

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Featured Application: This work has an important direct application for teachers or educational institutions working with Moodle, because it provides an open access software application, UBUMonitor, which facilitates the detection of students at risk.

Abstract: In this study, we used a module for monitoring and detecting students at risk of dropping out. We worked with a sample of 49 third-year students in a Health Science degree during a lockdown caused by COVID-19. Three follow-ups were carried out over a semester: an initial one, an intermediate one and a final one with the UBUMonitor tool. This tool is a desktop application executed on the client, implemented with Java, and with a graphic interface developed in JavaFX. The application connects to the selected Moodle server, through the web services and the REST API provided by the server. UBUMonitor includes, among others, modules for log visualisation, risk of dropping out, and clustering. The visualisation techniques of boxplots and heat maps and the cluster analysis module (*k*-means ++, fuzzy *k*-means and Density-based spatial clustering of applications with noise (DBSCAN) were used to monitor the students. A teaching methodology based on project-based learning (PBL), self-regulated learning (SRL) and continuous assessment was also used. The results indicate that the use of this methodology together with early detection and personalised intervention in the initial follow-up of students achieved a drop-out rate of less than 7% and an overall level of student satisfaction with the teaching and learning process of 4.56 out of 5.

Keywords: at-risk student; clustering; visualisation; self-regulated learning; Moodle; learning analytics

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1. Introduction

The contemporary teaching–learning process is increasingly carried out in e-learning or blended learning environments, and rarely face to face (F2F) only. This situation has been intensified by the COVID-19 crisis [1]. However, e-learning teaching has a series of challenges, among which the following stand out: interaction between teachers and students and between students themselves, customisation of the teaching–learning process, detection of students at risk, and the use of technological resources in learning management systems (LMSs) carried out from a good pedagogical setting. Although this type of teaching has several advantages over F2F teaching, LMSs allow all the interactions (collaborative between participants and between participants and learning objects) that take place during the teaching–learning process to be recorded [2]. However, one of the greatest risks is the early drop-out. In order to avoid this, monitoring systems of the student's learning process must be included in LMSs in order to carry out early detection and to make proposals for personalised tutoring. This is an essential factor in achieving effective learning [3,4]. Nevertheless, the monitoring systems must be carried out with the use of technological resources and artificial intelligence techniques that facilitate the interpretation of the students' learning behaviours. Supervised learning such as predictive methods, and unsupervised learning such as clustering techniques have been shown to be very useful [5,6]. However, current LMSs, such as Moodle, do not have enough detection tools incorporated, because the learning analytics (LA) of the logs they offer is very simple and does not give the teacher sufficient information about these processes [7]. In particular, student drop-out at university is one of the major concerns of teachers and university rectors worldwide. Some studies [8] have analysed the possible causes and have specified that the factors can be related to students, teachers, the university system, or be an interaction of all of them. Among the causes specific to students, motivation stands out; amidst those specific to teachers, the quality of teaching and the enhancement of student motivation towards learning are the most common issues; and with respect to the institution, the quality of university management is the main aspect. The factors that may be influencing the lack of students' motivation which can be detected by technological systems included in the LMS are the frequency of access to the platform to different resources and activities. This frequency is obtained from the analysis of logs. The knowledge of these data throughout the learning process will be a very useful tool for a teacher in the prevention of school dropout [2].

Therefore, it is important to detect students at risk early, for which educational data mining (EDM) techniques can be applied [5,9]. These will allow the prediction of the profile of the student at risk [9,10]. It has been proven that with these techniques, the prediction percentage is in the range of 79–83% [11]. Additionally, it has been found that the use of teaching methodology in virtual environments based on self-regulated learning (SRL) [12] together with project-based learning (PBL) [13,14] and the use of continuous assessment methodology [15] are predictors of the achievement of effective learning (60.4%) [16] and decrease the dropout rate [15,17]. In summary, these studies indicate that one of the ways to decrease the percentage of students who drop out of university is to have systems in the LMS that facilitate the detection of the student at risk throughout the teaching–learning process [18,19]. The functionalities of the LA and EDM will be analysed below. The most important contribution of this work is the use of a personalised tool, which connects directly to Moodle and facilitates the monitoring of the behaviour of each student throughout the teaching–learning process in each subject and enables the analysis of logs in a simple way through EDM techniques and visualisation within the tool itself. In previous studies for the detection of students at risk, the process was slower and more laborious because EDM techniques had to be applied in statistical analysis software outside the LMS or not directly connected to it [20].

1.1. Learning Analytics Procedures

LMSs include simple procedures for analysing logs produced during the teaching–learning process which can be consulted in various reports. These reports use techniques of frequency analysis and descriptive statistics (mean and standard deviation of observations), and the most advanced ones include an analysis of minimum and maximum ranges and distribution asymmetry and kurtosis. All this information is offered from visualisation tools and can provide the teacher with information about how the learning process is developing in their students [21]. However, these reports do not allow a visual and fast detection of the student at risk [22] and require the teacher to have knowledge of data processing and analysis from the use of EDM techniques. This is obviously a problem for the early prevention of the at-risk student. A further step in the analysis of logs has been taken with the incorporation of plugins that are inserted in LMSs [2,23–31] and facilitate the analysis and interpretation of the logs. The use of these tools provides a series of advances in the organisation and interpretation of the data and in the detection of the student at risk in the different learning objects (activities and resources), because it allows the teacher to choose the standard deviation (SD) that they consider to be an indicator of the detection of at-risk students (1, 2, 3, etc., SD) in their subject. Although these resources have a number of disadvantages, because they require the teacher to have some knowledge of Moodle management and data analysis, the results which they provide are very simple and do not normally include EDM techniques. Previous studies have applied supervised learning EDM techniques; particularly, prediction for the detection of at-risk students. Specifically, in the 2019 study by Sáiz-Manzanares et al. [11], it was found that the use of a personalised learning methodology in Moodle predicted 42.3% of the learning outcomes and 74.2% of the learning behaviours of students in the Moodle platform. Likewise, in the study by Sáiz-Manzanares et al. in 2020 [2], progress was made in the analysis of the logs using data visualisation tools on the prediction variables, in this case the type of degree and the assignment clusters with respect to the learning outcomes. However, these analyses were not carried out in the Moodle platform, and it was necessary to extract the logs and enter them in the Orange data mining tool. Therefore, the present work proposes to use a Moodle connection tool that allows the automatic application of these visualisation techniques.

1.2. Educational Data Mining (EDM) Procedures

As already indicated, the analysis and interpretation of the logs generated in LMSs has certain difficulties and requires the teacher to have skills in the use of data extraction and interpretation techniques [32]. If LMSs included EDM and data visualisation techniques [21,33], this would make it easier to detect the student at risk. EDM procedures include different techniques, one of the simplest being frequency analysis with heat maps [34]. This is a visualisation technique that allows users to see the frequencies of the accesses to the different resources of the LMS in different colours, creating a heat map. The variation of the colours is made by tone and intensity, offering the teacher quick visual information of the results. Additionally, it allows the detection of outliers (both above and below the average frequency) in different learning objects (resources and activities) on the platform. An example of a heat map visualisation is shown in Figure 1; in this case, the dark red colour indicates the students at maximum risk, i.e., with zero participation values, the light red colour indicates the students in the first quartile, the dark ochre colour represents the students in the second quartile, the light ochre colour is the students in the third quartile, the light green colour shows the students in the fourth quartile, and the dark green colour indicates the students with the highest participation value in Moodle.

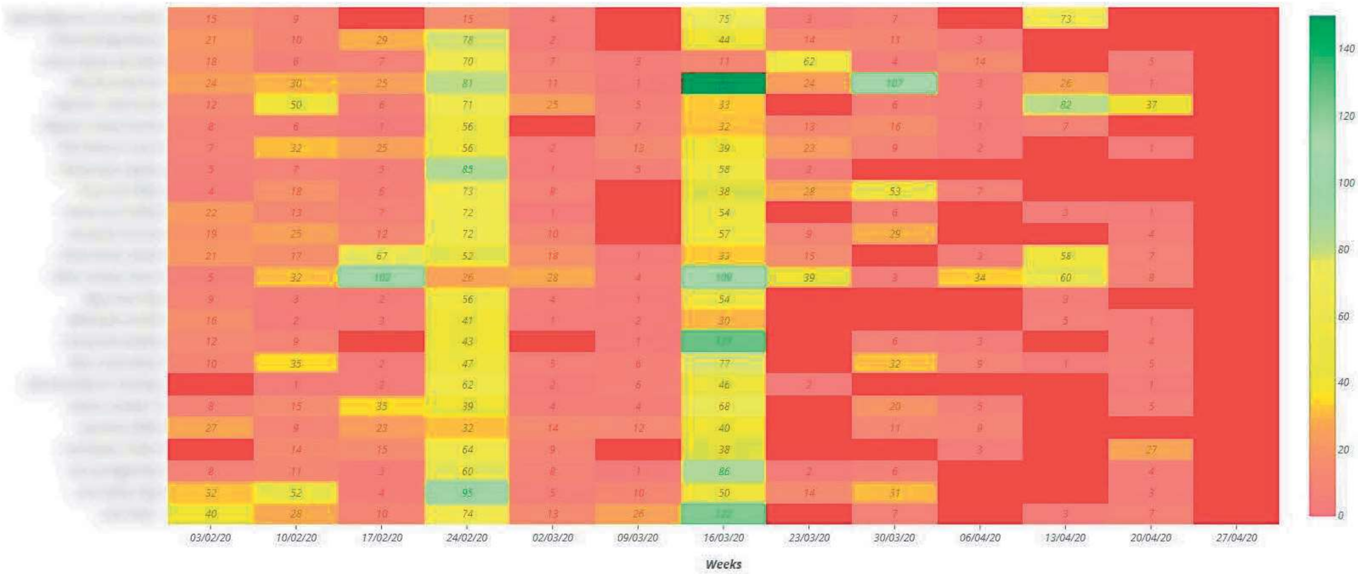

Figure 1. Heat map of weekly student monitoring in Moodle using UBUMonitor [35].

Besides, more complex EDM techniques such as supervised learning can be used [36,37]. These guide the prediction of the student at risk according to different variables or attributes. For this purpose, classification techniques (e.g., support vector machine, discriminant analysis, Bayesian networks and nearest neighbour, decision trees, neuronal networks, ensemble methods) and prediction techniques (linear regression, regression trees, support vector machine, etc.) can be used [38]. Similarly, within the unsupervised learning techniques, clustering techniques are included [33], in which the *k*-means, *k-means* ++, fuzzy *k*-means, and DBSCAN (density-based spatial clustering of applications with noise) algorithms [39] stand out. In this article, we will look more closely at the use of clustering techniques, because they facilitate the analysis of student learning behaviour in LMSs [33]. Moreover, they facilitate the detection of groups of students according to the different behaviours in the different learning objects (resources and activities). One of the most widely used algorithms is *k*-means [33]. With an X-set and a distance measure d: $X \times X \rightarrow \mathbb{R}$. The output of the *k*-means algorithm is a set of centres $C = \{c_1, c_2, \ldots, c_k\}$ which implicitly define a set of clusters in which each point belongs to the cluster represented by the nearest centroid, $\Phi = c(x) = argmin_{c \in C}$, d(x, c); the aim is to find the C-set that minimises the sum of the squared distances (see Equation (1)).

$$\sum_{x \in X} d(\Phi_C\,(x), x)^2 \tag{1}$$

The problem that *k*-means is trying to solve is to find the groupings that minimise the distance within each group, although this is an NP-hard problem. In practice, *k*-means is very fast, but it often gets stuck in local minima, so it may be useful to repeat the execution several times. A variant is the *k-means* ++ algorithm, which intelligently initialises the centroids to accelerate the convergence of the algorithm [40]. Other clustering algorithms are fuzzy *k*-means [22] and density-based spatial clustering of applications with noise (DBSCAN). Fuzzy *k*-means also tries to minimise the same objective function described on Equation (1), but in this case, the membership of an instance to a cluster is not strict, but rather it is fuzzy; the membership of an instance to a cluster is a function that can take values between 0 and 1. Both *k-means* ++ and fuzzy *k*-means require setting the number of clusters a priori, which is admissible if there is good intuition about how many clusters are present in the dataset, but otherwise it can be a problem. Furthermore, these methods also assume that the clusters are globular, because the methods compute centroids and assign each and every one of these instances to the nearest centroid, there being the possibility of considering some instances which do not belong to a cluster. Density-based spatial clustering of applications with noise (DBSCAN) is a data clustering algorithm proposed by Ester et al. [39]. The algorithm assumes that the clusters are regions with a high density of points. Unlike the previous algorithms, it does not assume that every point in the dataset must necessarily belong to a cluster, and some examples can be classified as noise. In DBSCAN, clusters do not need to be globular; although it is not necessary to establish a correct number of clusters, it is needed to set an Epsilon parameter used to determine which instances belong to a grouping or are on the contrary noise. Other advantages are its stability—DBSCAN is stable across different runs—and its scalability, with it being an algorithm capable of working with very large datasets.

Based on the above-mentioned research, the objectives of this study were:

1. Apply an external logs analysis tool in Moodle to detect students at risk over the course of a semester in different phases (initial, intermediate, and final);
2. Detect in the sample, with an external log analysis tool in Moodle, the clusters in different phases (initial, intermediate, and final) differentiating by type of algorithm (*k*-means ++, fuzzy *k*-means, DBSCAN);
3. Check if there were differences in the clusters found depending on the type of algorithm (*k*-means ++, fuzzy *k*-means, DBSCAN);
4. To check students' satisfaction with the teaching process and the monitoring of learning.

The research questions (RQ) related to the objectives are:

RQ1: There will be different activity clusters in the Moodle platform depending on the log collection phases (initial, intermediate, and final);

RQ2: There will be differences in the groupings obtained in the clusters in the log collection phases (initial, intermediate, and final) depending on the algorithm applied (*k*-means ++, fuzzy *k*-means, DBSCAN);

RQ3: There will be differences in the clustering obtained in the log collection phases (initial, intermediate, and final) depending on the applied algorithm (*k*-means ++, fuzzy *k*-means, DBSCAN) providing a better fit in the DBSCAN algorithm;

RQ4: Students will perceive the monitoring of their learning performed with the UBUMonitor application as reflected in high levels of satisfaction in the Questionnaire of Student Opinion on Quality of Teaching (QSOQT).

2. Materials and Methods

2.1. Participants

Convenience sampling was used, which previously found the estimated sample size over the total student population (n = 64) at a 90% confidence level, with a 3% precision and a 5% ratio of 44, with an expected 10% loss ratio, with an adjusted sample of 49 students [40]. In this study, a sample of 49 students (41 females and 8 males) was used. Table 1 presents the descriptive statistics of the sample with respect to the age variable and the gender disaggregation.

Table 1. Characteristics of the sample.

n **(Students)**	**Students Gender**							
	Women				**Men**			
	n	**%**	**Mage**	**SDage**	***n***	**%**	**Mage**	**SDage**
49	41	83.67	22.37	2.19	8	16.32	21.63	1.77

Note. Mage, mean age; SDage, standard deviation age; *n*, number of participants in each group; *n* (students), total number of participants.

2.2. Instruments

2.2.1. UBUMonitor Tool.

UBUMonitor [35] is a desktop application executed on the client, implemented with Java, and with a graphic interface developed in JavaFX. The application connects to the selected Moodle server, through web services and the REST API provided by the server. In the absence of web services to some specific data recovery, web scraping techniques are additionally used. All communication between the Moodle server and the UBUMonitor client is encrypted by HTTPS protocol for security reasons. As a result of these queries, the data are obtained in JSON and CSV format and are processed and transformed in the client into Java objects. For the visualisation of the collected data, the hybrid solution of applying Java and embedding web pages with different graphic JavaScript libraries, within the desktop application, is used. The data can be saved on the client to optimise access times in subsequent queries and offline access to the data, using the serialisation mechanism available in Java. The serialised files with the subject data are stored encrypted with the Blowfish algorithm [41]. A diagram of the operation of the tool can be found in Figure 2. This application is open source and free of charge and includes four modules: (1) visualisation module (allows an analysis of the access frequencies in components, events, sections, or course seen in Moodle) with options to analyse logs in different graphics (boxplot, etc.). All the visualisation options allow the export in graphic format and in .csv format, for the elaboration of reports and their subsequent analysis with other tools; (2) the comparison module analyses the student logs in the components, events, sections or course seen in Moodle, grades and completion of activities, giving information about the frequencies from a visual comparison in ranking and in evolution analysis of the selected students); (3) risk of dropping out module (gives information by intervals (0–3 days, 3–7 days, 7–14 and more than 7 days) about students' access to the subject and about access to the Moodle platform; (4) clustering module allows finding the clusters from different algorithms (*k-means* ++, fuzzy *k*-means, DBSCAN, MutiMeans++, etc.) and from different distances (Euclidean, Manhattan, etc.) that are processed from two Java libraries [42,43].

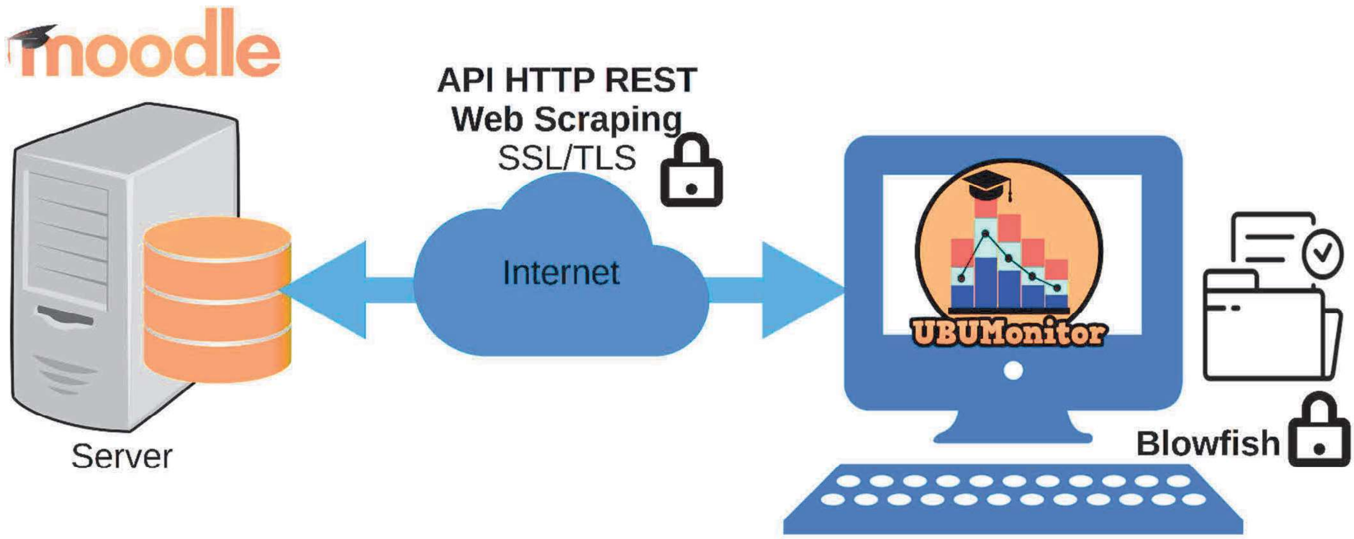

Figure 2. Diagram of the operation of the UBUMonitor [35].

2.2.2. Teaching Methodology

A methodology based on SRL and PBL was used [44], and a continuous assessment system that included 5 assessment procedures were implemented in the Moodle platform (UBUVirtual). Teaching was carried out in the second half of the 2019–2020 academic year, coinciding with the lockdown due to the state of alarm caused by COVID-19 decreed in Spain on March 14, 2020.

2.2.3. Questionnaire of Student Opinion on Quality of Teaching—QSOQT—by Bol, Sáiz and Pérez-Mateos (2012).

QSOQT [45] it is a survey based on the Student Evaluation of Educational Quality (SEEQ)—Short version by Herbert Marsh [46]. This is an opinion survey that contains 11 closed questions measured on a Likert-type scale from 1 to 5 (total reliability of the scale $\alpha = 0.92$) distributed in the following clusters: student motivation (1 item) ($\alpha = 0.75$), subject materials (3 items) ($\alpha = 0.80$), continuous assessment (2 items) ($\alpha = 0.80$), student perception of teacher motivation (3 items) ($\alpha = 0.77$), student perception of coursework (1 item) ($\alpha = 0.97$), and overall satisfaction with teaching (1 item) ($\alpha = 0.92$). This survey is available in open access [47] and has been validated by obtaining an overall reliability index of $\alpha = 0.92$ and by the components student motivation $\alpha = 0.91$, subject materials $\alpha = 0.91$, continuous assessment $\alpha = 0.91$, student perception of teacher motivation $\alpha = 0.91$, student perception of coursework $\alpha = 0.93$, and overall satisfaction with teaching $\alpha = 0.92$. It also includes two open questions: "Which of this teacher's characteristics has been the most important for your learning?" and "How do you consider that the teaching and assessment has been adapted during the special situation period by the COVID-19?"

2.3. Procedure

Authorisation was obtained from the Bioethics Committee of the University of Burgos (No. IR 30/2019). Student participation was voluntary and without financial compensation. Written informed consent was obtained from all participants. Work was carried out during the second semester of the academic year 2019–2020. The methodology applied was PBL and SRL [44] on a Moodle platform (UBUVirtual) with a continuous assessment procedure throughout the development of the course [2]. The semester concentrated on a nine-week duration and three follow-up measurements were carried out: an initial measurement (after two weeks), an intermediate measurement (after four weeks), and a final measurement (after eight weeks). The initial measurement was carried out after two weeks, because during this period, the students were able to see resources and carry out activities. This gives the teacher an indicator of whether there are any students who have not done so as often as expected. A measurement was also taken in the fourth week, because this would be the halfway point in the subject course and the teacher can check the evolution of their students and whether the measures they have implemented in the case of students in which problems were detected in the initial measurement have been useful and have prevented non-participation. If not, other actions can be employed to achieve this aim. Finally, the last measurement was carried out in the penultimate week of the course to check the development of all the students in the LMS and to see whether the measures or actions implemented in the initial and intermediate measurement have made it possible for the students at risk to be incorporated at a satisfactory pace of interaction and achievement of the academic competences. The UBUMonitor tool [35] was then used to monitor the students in Moodle. The analyses described in Section 2.4 were then applied.

2.4. Statistical Analysis

A descriptive-correlational design was applied. In order to contrast the objectives, frequency analysis (heat maps) and unsupervised learning techniques were applied (the aim was to find out the groupings of students at three points in the teaching–learning process (initial, intermediate, and final), in particular cluster analysis (*k-means* ++, fuzzy *k*-means, DBSCAN); unsupervised learning techniques were applied because the aim was to find out the groupings of students at three points in the teaching–learning process, initial, intermediate, and final. Additionally, we have applied the Manhattan distance. This is the distance between two points p and q as the sum of the absolute differences between each dimension; this measure is less affected by outliers and is sturdier than the Euclidean distance because it does not square the differences. Strictly speaking, *k*-means using the Manhattan distance is not *k*-means because the centroids are no longer means. Nevertheless, we still use that name. Several implementations of the *k*-means method allow to use different distances and they do not change its name. Also, theFriedman Test for k-dependent samples is applied to check whether the allocation differences between the three clusters and goodness-of-fit indices to analyse the adjusted between different clustering algorithms. In addition, we have included the adjusted Rand Index. The SPSS v.24 [48] statistical package, AMOS v.24 [49], and the UBUMonitor monitoring tool (35) that includes two Java clustering libraries [42,43] were used to perform the analyses. The qualitative analysis of the QSOQT open-ended questions was performed using word cloud and sentiment analysis with ATLAS.ti v.9 [50].

3. Results

To check the first objective, the UBUMonitor [35] tool was used to analyse the logs of Moodle v.3.8 (UBUVirtual platform of the University of Burgos). The description of the tool can be found in Section 2.2.1. The semester started on (February 3, 2020) and the initial measurement was made after two weeks (February 17, 2020), the intermediate measurement after four weeks (March 2, 2020) and the final measurement after eight weeks (March 30, 2020). The components Assignment, Feedback, File, File submissions, Folder, Glossary, Quiz and URL were analysed. The formats chosen were boxplots (see Figure 3) and heat maps (see Figure 4). In all the visual analyses, if the teacher was positioned at the top or at the bottom, they could see the name of the student and detect the student at risk (outliers at the bottom) or the student with high performance (outliers at the top). Additionally, a frequency analysis could be performed on the heat hap to visually detect those students where the interaction had been marked in red. This tool allows, besides the visualisation of the data, the export of them to a .csv file.

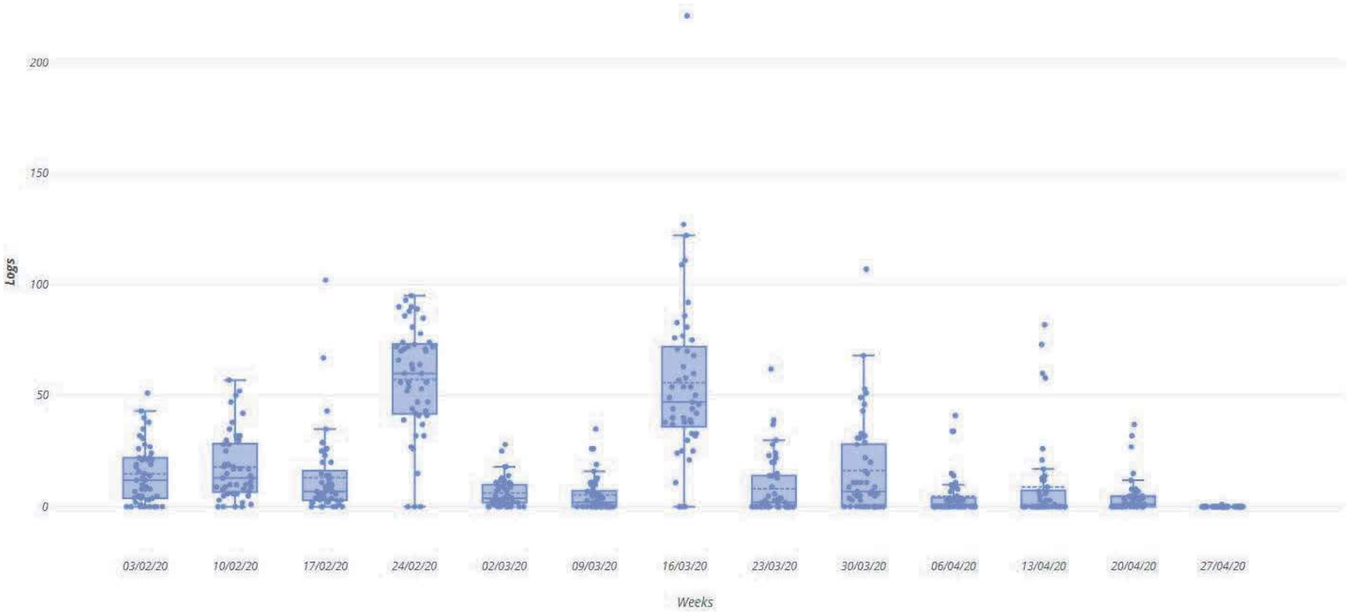

Figure 3. Boxplot of the weekly monitoring of students and detection of outliers in Moodle carried out with UBUMonitor [35].

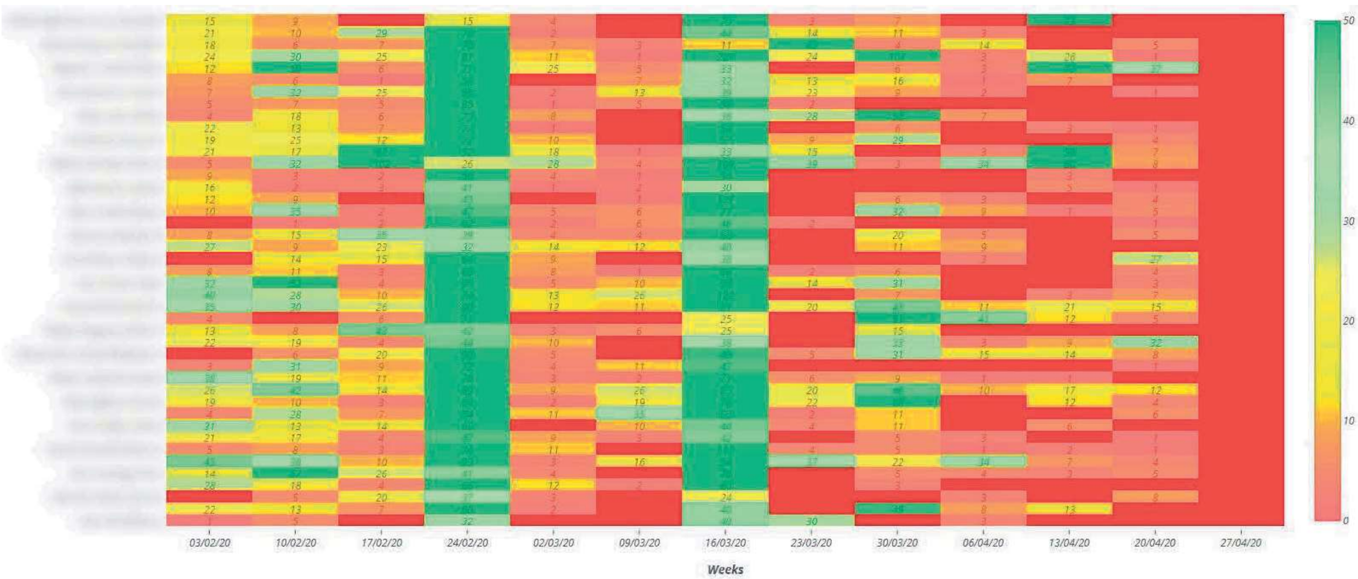

Figure 4. Heat map of the weekly monitoring of students and detection of outliers in Moodle carried out with UBUMonitor [35].

In order to check the second and third objectives and RQ2 and RQ3, firstly, the clusters were found with the three algorithms used (*k*-means ++, fuzzy *k*-means and DBSCAN) in the three periods of initial measurement (see Figure 5), intermediate measurement (see Figure 6), and final measurement (see Figure 7). These figures are the result of applying a principal component analysis (PCA). DBSCAN's plots show some grey points because they are not assigned to any cluster. Only two components were used because the third component only explained 0.04 more of the variance in the initial measurement, 0.02 in the intermediate measurement, and 0.01 in the final measurement. It was also found that the initial assessment explained 94.4% of the variance, the intermediate measurement 96.3%, and the final measurement 98.3%. Moreover, it should also be noted that graphs with three components are more difficult to visualise.

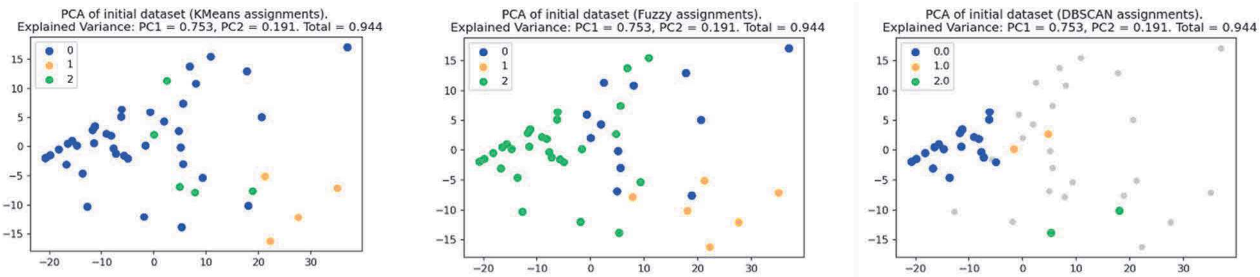

Figure 5. Cluster analysis in the initial measurement (two weeks after the beginning of the semester) with the *k*-means ++, fuzzy *k*-means, density-based spatial clustering of applications with noise (DBSCAN) algorithms.

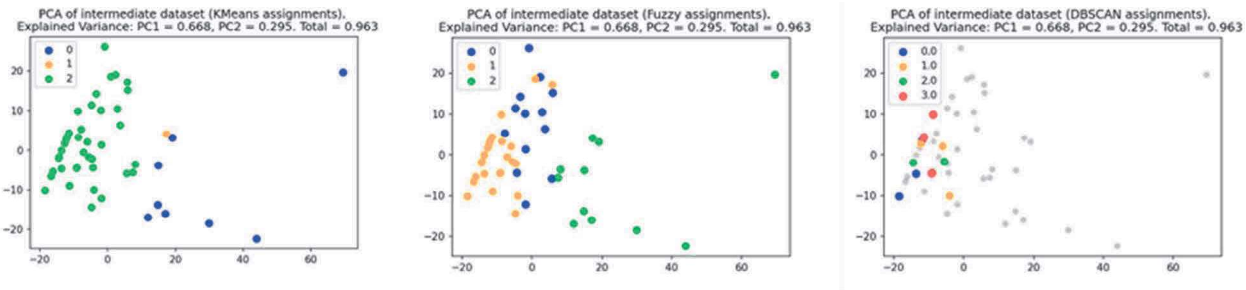

Figure 6. Cluster analysis in the intermediate measurement (four weeks after the beginning of the semester) with the *k*-means ++, fuzzy *k*-means, DBSCAN algorithms.

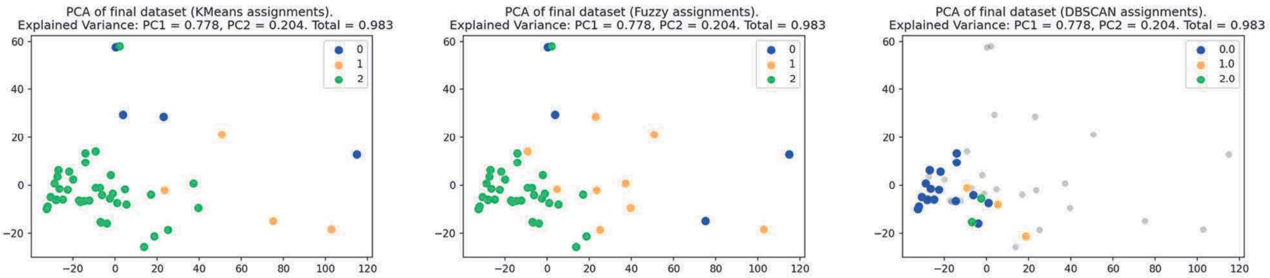

Figure 7. Cluster analysis in the final measurement (eight weeks after the beginning of the semester) with the *k*-means ++, fuzzy *k*-means, DBSCAN algorithms.

The adjusted Rand Index was applied; the result is a measure of how similar two clusterings for the same data are. An adjusted Rand index has a value between −1 and 1, with 1 indicating that the two data clusterings agree exactly on every pair of points, and 0 is the expected value for randomly created clusters. DBSCAN does not always assign a cluster to an instance; therefore, for this calculation, it has been considered that all the instances labelled as noise are assigned to an additional cluster. The most similar clusters according to the metric are *k*-means ++ (with the final dataset) and fuzzy *k*-means (also with the final data set). Usually, adjusted Rand index is used when the correct clusters are known, comparing them with the clusters obtained by some method. In our case, we are in a truly unsupervised setting, and the correct clusters are unknown. Hence, the adjusted Rand index has been used to compare the clustering obtained with different methods and/or moments. In Table 2 is presented the matrix of adjusted Rand index, the colours indicating the degree of relationship; blue represents a low relationship (interval 0–>0.20), orange represents an intermediate relationship (interval 0.20–>0.50), and green represents a high relationship (interval < 0.50–1).

Table 2. Adjusted Rand index matrix.

	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
1	1	0.14	0.30	0.45	0.14	0.22	0.008	−0.13	−0.02
2	0.14	1	0.17	0.09	0.34	0.12	−0.05	−0.18	0.02
3	0.30	0.17	1	0.09	0.03	0.62	−0.04	−0.12	−0.03
4	0.45	0.09	0.09	1	0.14	0.13	0.28	−0.09	−0.03
5	0.14	0.34	0.03	0.14	1	0.09	0.02	−0.06	0.02
6	0.22	0.12	0.62	0.13	0.09	1	−0.04	−0.11	0.05
7	0.008	−0.05	−0.04	0.28	0.02	−0.04	1	−0.03	0.11
8	−0.13	−0.18	−0.12	−0.09	−0.06	−0.11	−0.03	1	0.04
9	−0.02	0.02	−0.03	−0.03	0.02	0.05	0.11	0.04	1

Note. 1 = *k*-means ++ Initial; 2 = *k*-means ++ Intermediate; 3 = *k*-means ++ Final; 4 = fuzzy *k*-means Initial; 5 = fuzzy *k*-means Intermediate; 6 = fuzzy *k*-means Final; 7 = DBSCAN Initial; 8 =DBSCAN Intermediate; 9 = DBSCAN Final.

In addition, a goodness-of-fit index was then applied [51]. No perfect fit was found in any of the algorithms, although the DBSCAN algorithm was the best fit in the Akaike information criterion (AIC) and parsimony index (ECVI) indicators (see Table 3). In order to check whether the allocation differences between the three clusters were significant, the Friedman test for k-dependent samples was applied. No significant differences were observed between the three algorithms in the three measurements (see Table 4).

Table 3. Goodness-of-fit indexes of the *k*-means ++, fuzzy *k*-means and DBSCAN algorithms.

Goodness-of-Fit Index	*k*-Means ++	Fuzzy *k*-Means	DBSCAN	Accepted Value
df	24	24	24	
χ^2	102.47 *	96.750 *	91.588 *	* $p > 0.05$ $\alpha = 0.05$

RMSEA	0.261	0.251	0.242	>0.05–0.08
RMSEA Interval (90%)	0.210–0.341	0.200–0.305	0.191–0.296	
SRMR	0.196	0.205	0.00	>0.05–0.08
TLI	0.704	0.628	0.704	0.85–0.90<
IFC	0.803	0.752	0.803	0.95–0.97<
AIC	162.47	156.750	151.588	The lowest value
ECVI	3.385	3.266	3.158	The lowest value
ECVI interval (90%)	2.810–4.117	2.712–3.977	2.624–3.850	The lowest value

Note. * $p < 0.05$; df, degrees of freedom; χ^2, Chi-squared; RMSEA, root-mean-square error of approximation; SRMR, standardised root-mean-square residual; TLI, Tucker–Lewis index; CFI, comparative fit index; AIC, Akaike information criterion; ECVI, parsimony index.

Table 4. Analysis of the differences with the Friedman test for k-dependent samples between the results of grouping students in the three clusters in the initial, intermediate, and final measurements.

Cluster	Measurement	Mean	SD	Max	Min	MRange	χ^2	*gl*	*p*
	Initial								
k-means ++		13.00	13.46	2	28	1.83	0.55	2	0.76
Fuzzy *k*-means			9.45	9	27	2.33			
DBSCAN		12.67	17.62	2	33	1.83			
	Intermediate								
k-means ++		16.33	17.21	4	36	2.17	0.55	2	0.76
Fuzzy *k*-means		16.33	15.70	4	34	2.17			
DBSCAN		14.67	21.08	2	39	1.67			
	Final								
k-means ++		16.33	23.18	1	43	2.33	2.00	2	0.37
Fuzzy *k*-means		16.33	11.06	6	28	2.33			
DBSCAN		13.33	21.39	0	38	1.33			

Note. $p < 0.05$; Initial measurement (after two weeks); Intermediate measurement (after four weeks), Final measurement (after eight weeks); SD, standard deviation; χ^2, Chi-squared; Max, maximum; Min, minimum; MRange, mean range.

In summary, the behaviour of the students on the platform depending on the analysis period (initial, intermediate, and final) was different and a higher activity was detected in the initial period and in the intermediate period, falling in the final measurement period (see Figure 8).

Figure 8. Graph of the evolution of the risk of abandonment (not access to the LMS) over the semester and analysed by week using the UBUMonitor tool [35].

This evaluation is sensible because the course uses the PBL methodology, and the initial and medium period is where students should have a greater interaction with the resources of the LMS; in the final period, the students are preparing the presentation of the project and the interaction in the platform is less.

Regarding the fourth objective and RQ4, it was found in QSOQT [45] that there was an average general satisfaction of 4.56 out of 5 (SD = 0.63), and disaggregated by components it was 4.38 out of 5 (SD = 0.62); 4.58 out of 5 (SD = 0.58) in subject materials; 4.38 out of 5 (SD = 0.72) in continuous assessment; 4.77 out of 5 (SD = 0.40) in student perception of teacher motivation; and 3.76 out of 5 (SD = 0.75) in the student perception of coursework. Student satisfaction with the subject was higher by an interval of 0.5–1.5 points above the average for the other subjects. On the other hand, the comments to the first and second open question were analysed with the qualitative analysis tool ATLAS.ti 9, for which a word cloud analysis (see Figure 9) and a sentiment analysis on a categorisation of positive negative and neutral feelings in each of the statements (see Figure 10) were carried out. These were found to have 25 frequencies (1 in negative categorisation, 5 in neutral categorisation, and 19 in positive categorisation).

(**a**) (**b**)

Figure 9. Word clouds on the answers to questions 1 (**a**) and 2 (**b**) in the QSOQT [45].

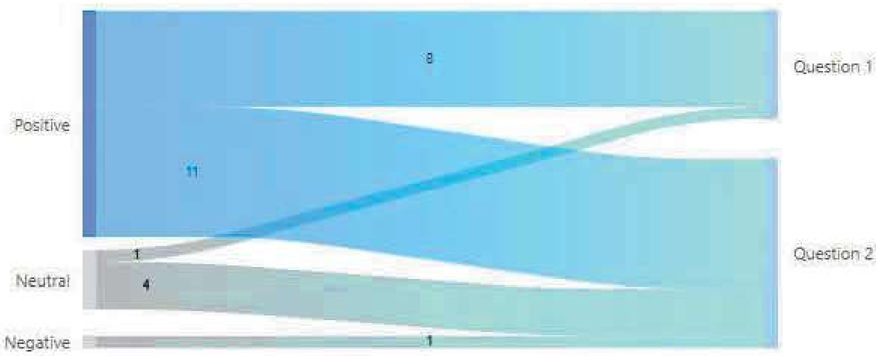

Figure 10. Sentimental analysis of answers to questions 1 and 2 in the QSOQT [45].

4. Discussion

The society of the 21st century is constantly developing, with technological advances occurring continuously and at great speed. The educational environment is one of the areas in which these technological advances have a great applicability, for which it is necessary to make changes in the methodology and teaching resources. An essential point, especially in Higher Education, is the way in which the teaching–learning process takes place. This process is increasingly taking place within LMSs, be it F2F teaching, blended learning, or e-learning. Therefore, teachers need tools to help them in their educational work, which must go beyond the transmission of knowledge, and in the monitoring of their students' learning processes. This monitoring, which in the past could be done through classroom observation, now requires the use of technological tools. This situation has become even more relevant and pressing due to the COVID-19 health crisis. Consequently, it can be concluded that it is important for LMSs to incorporate simple and easy-to-use student learning process monitoring systems for teachers in LMS teaching environments. In addition, these systems need to provide enough information for the early detection of students at risk. Such detection is the only possibility to prevent academic failure because it allows the teacher to offer personalised learning to the student. To this end, LMSs need to incorporate EDM and artificial intelligence techniques that facilitate accurate analysis and the visualisation of results. This will ensure that teachers can use these systems and interpret the results in order to make better decisions. Furthermore, it should not be forgotten that in addition to the need to incorporate simple, accurate and highly usable monitoring systems in the LMS, it is also important to ensure that the results of the LMS can be used by the teacher to make better decisions. Specifically, in this study, we have applied the UBUMonitor tool, which proved to be a very useful instrument for the detection of students at risk in the marked analysis periods (initial, intermediate, and final). The visualisation of the students' behaviours in the chosen components with the boxplot item and heat map graphics allowed the visualisation of the students that were at the extremes (above and below) in the different components used in the Moodle platform. This made it easier for the teacher to provide personalised tutoring to avoid early dropouts. Additionally, the clustering module of UBUMonitor made it possible to obtain the clusters with different algorithms. In this study the algorithms *k-means* ++, fuzzy *k*-means, and DBSCAN were used in the three analysis periods (initial, intermediate, and final). This functionality allowed the teacher to quickly analyse the grouping of students in different monitoring periods. In this work, different assignments were found between the three algorithms; these were not significant, although the best fit values were found with the DBSCAN algorithm [39].

5. Conclusions

In short, teaching in Higher Education is increasingly being done in blended learning or e-learning modes in LMSs (e.g., Moodle). This fact has been accelerated in the current health crisis caused by COVID-19, and LMSs are a way that enable the continuity of teaching in safe environments. For this reason, teachers need easy-to-use tools that help them to monitor the learning process and detect students at risk from an early stage. This detection enables teachers to offer personalised teaching through the aids that each student needs at each moment of the semester. In this study, the monitoring of students and personalised intervention has led to low drop-out rates (7%) and high student satisfaction with the teaching–learning process (4.56 out of 5). However, this research has the limitations of being a case study (application of the UBUMonitor tool to teaching in a specific subject). Nevertheless, its objective was to demonstrate a free access tool for the detection of students at risk and the prevention of early drop-out.

On the other hand, in this study, no significant differences in the fit between the three algorithms applied were found, although DBSCAN presented parameters closer to the correct fit, as pointed out in the studies by Ilieva and Yankova [22] and Arthur and Vassilvitskii [39]. However, when applying an unsupervised method, clustering, we do not know the perfect cluster. However, this aspect will be tested in further research with larger and more heterogeneous samples of students. These are the challenges that educational leaders and teachers at university level face in 21st century society, and to address them more research and funding is needed both in the improvement of LMS tools from the incorporation of student tracking modules that include artificial intelligence and data mining and the improvement of teacher training in active methodologies, SRL and continuous assessment systems within the LMS. In summary, it can be concluded that effective teaching in the 21st century society requires different technological and training resources that must go hand in hand in order to achieve a successful teaching–learning process.

6. Patents

Marticorena Sánchez, R., Peng Ji, Y., y Pardo Aguilar, C. (2019). UBUMonitor-Monitorización de alumnos en la plataforma Moodle (UBUMonitor-Monitoring of students on the Moodle platform). Intellectual Property Registry. Software. Ministry of Culture (Spain). N BU-107-19.

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Informed Consent Statement: Written informed consent was obtained from all subjects involved in the study.

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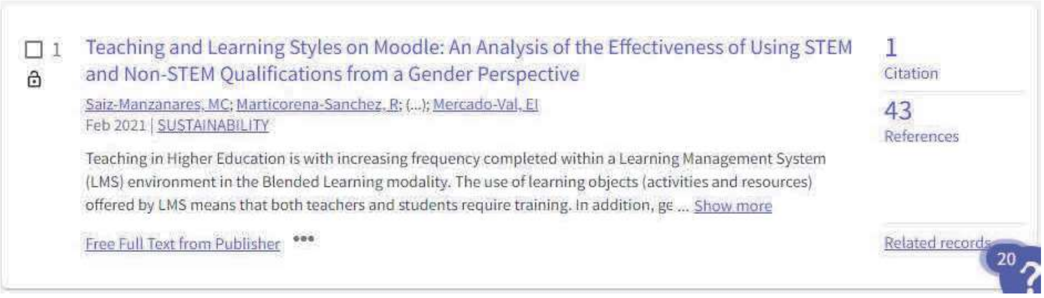

Figura 3.7: Citaciones del artículo 2. Fuente: WOS (31/07/2021)

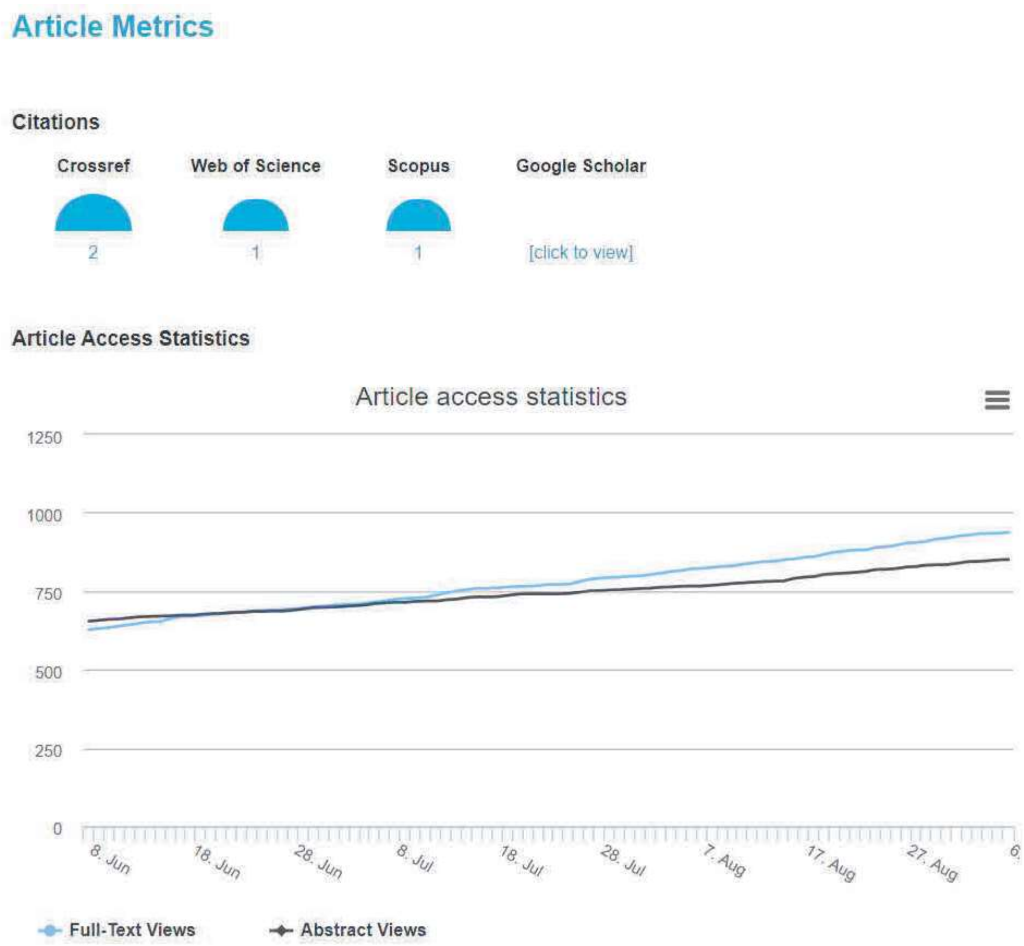

Figura 3.8: Estadísticas del artículo 2. Fuente: *Sustainability* (06/09/2021)

3.1.3.1. Estándares de calidad de la revista *Applied Sciences*

La revista está indexads en *Science Citation Index Expanded (WOS)*, Scopus y otras bases de datos.

Esta revista se encuentra en la base de datos *Journal Citation Report* en *Science Citation Index Expanded* (SCIE) dentro de la categoría *ENGINEERING, MULTIDISCIPLINARY - SCIE* en el segundo cuartil (Q2 JIF = 2.679) (Ver imagen 3.9). En el año 2020, en el momento en el que se publicó la aportación, la revista se situó en la posición 55 de 169 revistas, lo que la coloca en un Q2 con un *Journal Impact Factor* (JIF) de 2.679 y un *Journal Impact Factor Without Self Citations* de 2.219. En ESI en 2018 (último dato registrado en WOS) ocupa una posición de 211/893, es decir está en el primer cuartil (Q1).

Applied Sciences también está indexada en Scopus. La revista comienza a indexarse en 2011 en las categorías: *Computer Sciences and Materials Sciences Multidisciplinary Digital Publishing Institute* (MDPI). En 2015 registra un valor SJR (*Scimago Journal Rank*) de 1 =0.82, situándose en el primer cuartil de ambas categorías, actualmente tiene un H *index* de 23.

3.1.3.2. Estándares de calidad del artículo 3

Según datos de la WOS este artículo cuenta con 1 citación y 51 referencias como puede verse en la imagen 3.11.

En los registros de la métrica de la revista (ver figura 3.12) desde la fecha de su publicación 17 de marzo de 2021 el artículo ha sido visto en la página más de 750 veces y ha sido descargado 556 veces y registra 2 citas y un *altmetrics*.

3.1.4. Artículo 4: *Analysis of the Learning Process through Eye Tracking Technology and Feature Selection Techniques*

Applied Sciences (ISSN 2076-3417; CODEN: ASPCC7) es una revista interdisciplinaria de acceso abierto revisada por pares y publicada semestralmente en línea por el MDPI. Cubre las ciencias e ingeniería y la investigación aplicada. Acceso abierto y gratuito para los lectores, con gastos de procesamiento de artículos (APC) pagados por los autores o sus instituciones.

La revista *Applied Sciences* tiene alta visibilidad ya que está indexada en la WOS y Scopus. La publicación es rápida puesto que los manuscritos

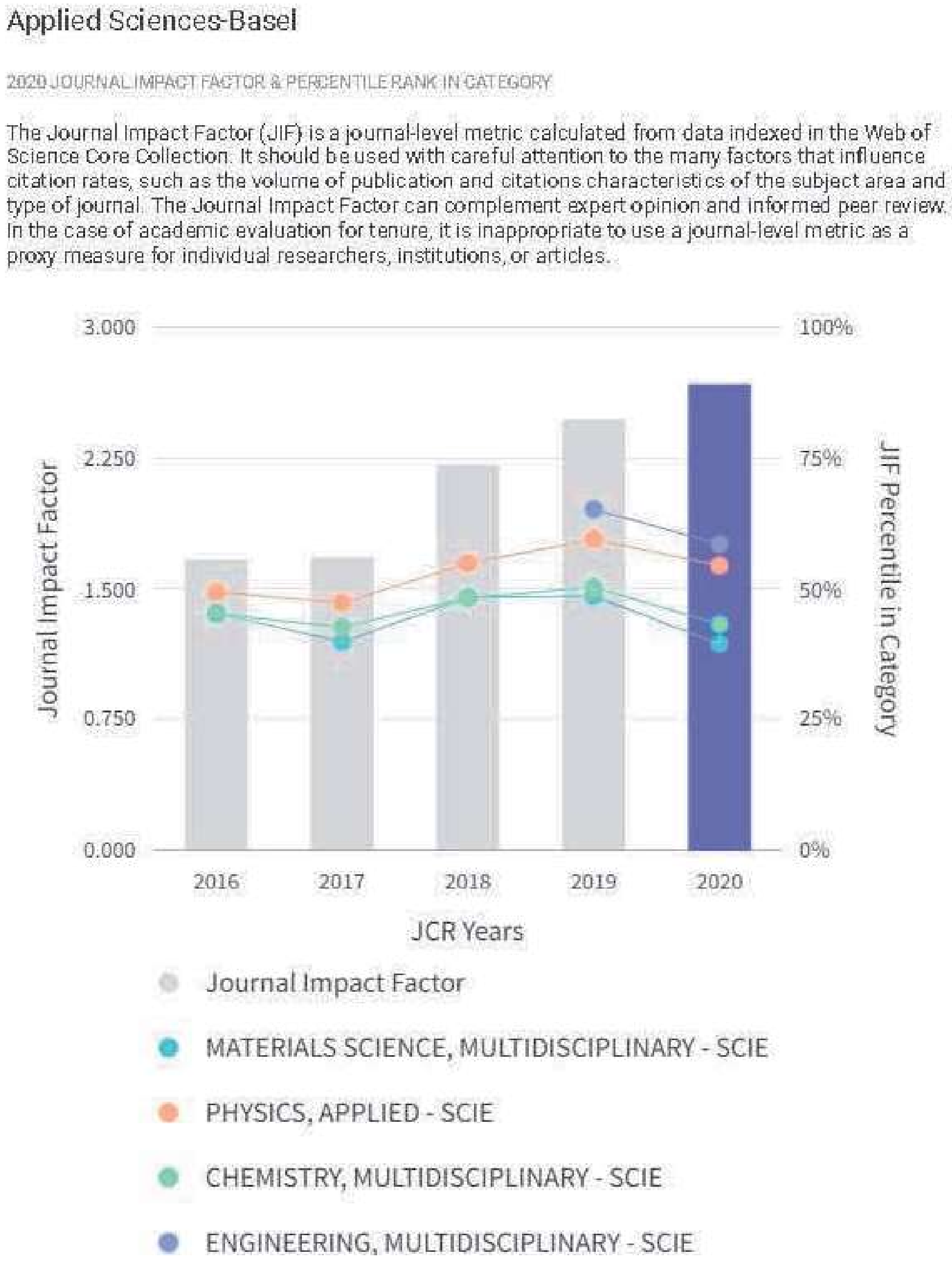

Figura 3.9: JIF de la revista *Applied Sciences* 1. Fuente: WOS (31/07/2021)

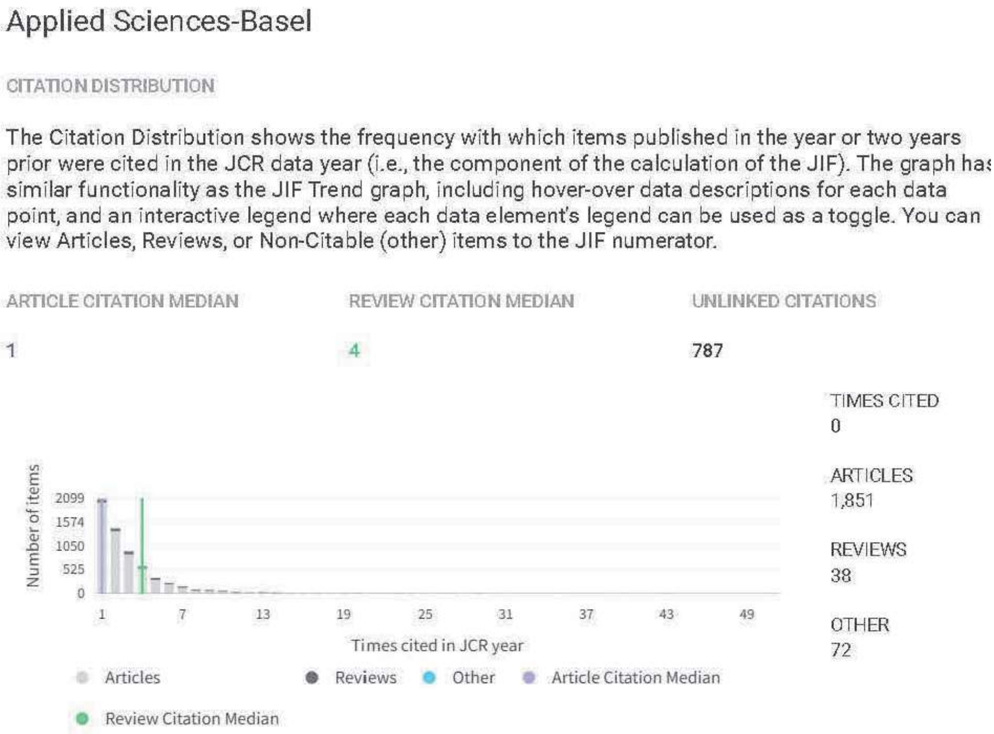

Figura 3.10: Citaciones de la revista *Applied Sciences* 1. Fuente: WOS (31/07/2021)

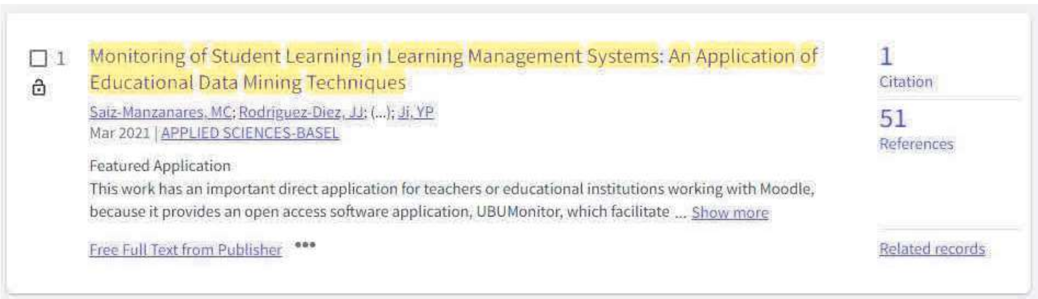

Figura 3.11: Citaciones del artículo 3. Fuente: WOS (31/07/2021)

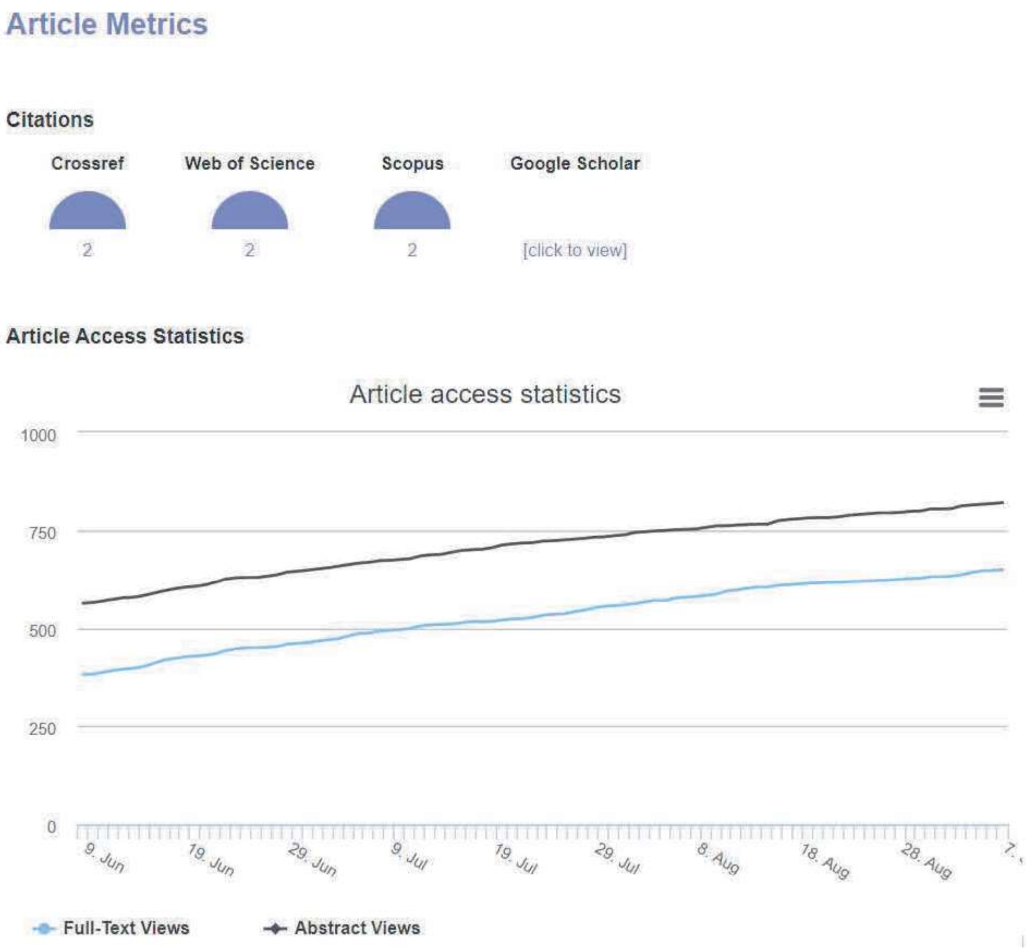

Figura 3.12: Estadísticas del artículo 3. Fuente: *Applied Sciences* (07/09/2021)

son revisados por pares y se proporciona una primera decisión a los autores aproximadamente 15.9 días después de su presentación; la aceptación de la publicación se realiza en 2,9 días (valores medianos para los artículos publicados en esta revista en el segundo semestre de 2019).

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Article

Analysis of the Learning Process through Eye Tracking Technology and Feature Selection Techniques

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Abstract: In recent decades, the use of technological resources such as the eye tracking methodology is providing cognitive researchers with important tools to better understand the learning process. However, the interpretation of the metrics requires the use of supervised and unsupervised learning techniques. The main goal of this study was to analyse the results obtained with the eye tracking methodology by applying statistical tests and supervised and unsupervised machine learning techniques, and to contrast the effectiveness of each one. The parameters of fixations, saccades, blinks and scan path, and the results in a puzzle task were found. The statistical study concluded that no significant differences were found between participants in solving the crossword puzzle task; significant differences were only detected in the parameters saccade amplitude minimum and saccade velocity minimum. On the other hand, this study, with supervised machine learning techniques, provided possible features for analysis, some of them different from those used in the statistical study. Regarding the clustering techniques, a good fit was found between the algorithms used (*k*-means ++, fuzzy *k*-means and DBSCAN). These algorithms provided the learning profile of the participants in three types (students over 50 years old; and students and teachers under 50 years of age). Therefore, the use of both types of data analysis is considered complementary.

Keywords: machine learning; cognition; eye tracking; instance selection; clustering; information processing

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1. Introduction

The eye tracking technique has represented an important advance in research in different fields, for example, cognitive psychology, as it records evidence on the cognitive processes related to attention during the resolution of different types of tasks. In particular, this technology provides the researcher with knowledge of the eye movements that the learner performs to solve different tasks [1]. This implies an important advance in the study of information processing, as this technique will allow us to obtain empirical indicators in different metrics, all of which offers a guarantee of precision to the psychology professional for the interpretation of each user's information processing. However, the measurements are complex and, above all, lengthy in time, which often means that the ratios of participants are not very large. In summary, technological advances are improving the study of information processing in different learning tasks. The use of these resources is an opportunity for cognitive and instructional psychology to delve into the analysis of the variables that facilitate deep learning in different tasks. In addition, these tools allow the visualisation of the learning patterns of apprentices during the resolution of different activities. Initial research in this field [2] indicated that readers with prior knowledge showed little interest in the images embedded in the learning material. Furthermore, recent research [3] has found significant differences in eye tracking behaviour between experts vs. novices. It seems that experts allocate their attention more efficiently and learn more easily if automated monitoring processes are applied in learning proposals. Similarly, other studies [2] have indicated that the use of multimedia resources that incorporate zoom effects makes it easier for information to remain longer in short-term memory (STM). Likewise, if this information is accompanied by a narrating voice, attention levels and semantic comprehension increase [4,5]. A number of methods are used to analyse the effectiveness of the learning process including eye tracking-based methods. This technique offers an evaluation of eye movement in different metrics [1–5]. The eye tracking technique can use different algorithms [6–9]. They can be used to extract different metrics (more detailed explanations are given below). Specifically, eye tracking technology allows the analysis of the relationship between the level of visual attention and the eye–hand coordination processes during the resolution of different tasks within the executive attention processes [7,8]. Clearly, rapid eye movement has also been associated with the learner's fixation on the most relevant elements of the material being learned [2].

In this context, attention is considered to be the beginning of information processing and the starting point for the use of higher-order executive functions. In the same way, observational skills relate to eye tracking, which is directly related to the level of arousal and the transmission of information first to the STM and then its processing in working memory [6]. This development is influenced by learner-specific variables such as age, level of prior knowledge, cognitive ability and learning style [7]. However, some studies show that prior knowledge can compensate for the effects of age [8]. On the other hand, eye tracking technology is one of the resources that is supporting this new way of analysing the learning process. This technology is centred on evidence-based software engineering (EBSE) [9]. This technological resource makes it possible to study attentional levels and relate them to the cognitive processes that the learner uses in the course of solving a task [10,11]. Thus, eye tracking technology provides different metrics based on the recording of the frequency of gaze on certain parts of a stimulus. These metrics can be previously defined by the researcher and are called areas of interest (AOI), which can be relevant or irrelevant. This information will allow the practitioner to determine which learners are field-dependent or field-independent, based on their access to irrelevant vs. relevant information [12]. Likewise, the use of multimedia resources, such as videos, which include Self-Regulation Learning (SRL) aids through the teacher's voiceover or the figure of an avatar seems to be an effective resource for maintaining attention and comprehension of the task and even compensating for the lack of prior knowledge of the learners. One possible explanation is that they enhance self-regulation in the learning process [13–15]. However, the design of learning materials seems to be a key factor in maintaining attention during task performance. Therefore, it is necessary to know which elements are relevant vs. irrelevant, not only for the teacher but also for the learners' perception [16]. This is why the knowledge of measurement metrics in eye tracking technology, together with their interpretation, is a relevant component for the design of learning activities for different types of users.

1.1. Measurement Parameters in Eye Tracking Technology

As mentioned above, eye tracking technology facilitates the collection of different metrics. First, it enables the recording of the learner's eye movement or eye tracker while performing an activity. In addition, the use of eye tracking technology allows the definition of relevant vs. non-relevant areas (AOI) in the information being learned [17]. Within these metrics, different parameters can be studied, such as the fixation time of the eye on the part of the stimulus (interval between 200 and 300 ms). In this line, recent studies [18] indicate that the acquisition of information is related to the number of eye fixations of the learner. Similarly, another important metric is the saccade, which is defined as the sudden and rapid movement of a fixation (the interval is 40–50 ms). Sharafi et al. [18,19] found differences in the type of saccade depending on the phase of information encoding the learner was at. Another relevant parameter is the scan path or tracking path. This metric collects, in chronological order, the steps that the learner performs in the resolution of the learning task within the AOI marked by the teacher [18,19]. Likewise, eye tracking technology allows the use of supervised machine learning techniques to predict the level of learners' understanding, as this seems to be related to the number of fixations [20]. Recent studies indicate that variability in gaze behaviour is determined by image properties (position, intensity, colour and orientation), task instructions, semantic information and the type of information processing of the learner. These differences are detected using AOIs that are set by the experimenter [21].

In summary, eye tracking technology records diverse types of parameters that provide different interpretations of the underlying cognitive processes during the execution of a task. These parameters fall into three categories: fixations, saccades and scan path. The first one, fixations, refers to the stabilisation of the eye on a part of the stimulus during a time interval between 200 and 300 ms. In addition, eye tracking technology provides information about the start and the end time in x and y coordinates. The meaning of the cognitive interpretation is related to the perception, encoding and processing of the stimulus. The second ones, saccades, refers to the movement from one fixation to another, which is very fast and in the range of 40–50 ms. The third ones, scan path, refers to a series of fixations in the AOIs in chronological order of execution. This cognitive metric is useful for understanding the behavioural patterns of different participants in the same activity. Furthermore, each of these metrics has its own measurement specifications. Table 1 below shows the most significant ones and, where appropriate, their relationship with information processing.

Table 1. Most representative parameters that can be obtained with the eye tracking technique and their significance in information processing.

Metric	Acronym	Metric Meaning	Learning Implications
Fixation Count	FC	Counts the number of specific bindings on AOIs in all stimuli	A greater number and frequency of fixations on a stimulus may indicate that the learner has less knowledge about the task or difficulty in discriminating relevant vs. non-relevant information. These are measures of global search performance [22].
Fixation Frequency Count	FFC		
Fixation Duration	FD	Duration of fixation	It gives an indication of the degree of interest and reaction times of the learner. Longer duration is usually associated with deeper cognitive processing and greater effort. For more complicated texts, the user has a longer average fixation duration. Fixation duration provides information about the search process [22].
Fixation Duration Average	AFD	Average duration of fixation	Longer fixations refer to the learner spending more time analysing and interpreting the information content within the different areas of interest (AOIs). The average duration is considered to be between 200 and 260 ms.
Fixation Duration Maximum	FDMa	Maximum duration of fixation	They refer to reaction times.
Fixation Duration Minimum	FDMi	Minimum duration of fixation	

Table 1. *Cont.*

Metric	Acronym	Metric Meaning	Learning Implications
Fixation Dispersion Total	FDT	Sum of all dispersions of fixations in X and Y	It refers to the perception of information in different components of the task.
Fixation Dispersion Average	FDA	Sum of all fixation dispersions in X and Y divided by the number of fixations in the test	It analyses the dispersions in each of the fixations in the different stimuli.
Saccades Count	SC	Total number of saccades in each of the stimuli	A greater number of saccades implies greater search strategies. The greater the breadth of the saccade, the lower the cognitive effort. It may also refer to problems in understanding information.
Saccade Frequency Count	SFC	Sum of all saccades	They refer to the frequency of use of saccades that are related to search strategies.
Saccade Duration Total	SDT	Sum of the duration of all saccades	
Saccades Duration Average	SDA	Average duration of saccades in each of the AOIs	It allows discriminating field-dependent vs. non-dependent trainees.
Saccade Duration Maximum	SDMa	Maximum saccade duration.	They refer to the perception of information in different components of the task.
Saccade Duration Minimum	SDMi	Minimum saccade duration.	
Saccade Amplitude Total	SAT	Sum of the amplitude of all saccades	Newcomers tend to have shorter saccades.
Saccade Amplitude Maximum	SAMa	Maximum of saccade amplitude	
Saccade Amplitude Minimum	SAMi	Minimum of the saccade amplitude	
Saccade Velocity Total	SVT	Sum of the velocity of all saccades	They are directly related to the speed of information processing in moving from one element to another within a stimulus.
Saccade Velocity Maximum	SVMa	Maximum value of the saccade velocity	
Saccade Velocity Minimum	SVMi	Minimum value of saccade speed	
Saccade Latency Average	SLA	It is equal to the time between the end of one saccade and the start of the next saccade	It is directly related to reaction times in information processing. The initial saccade latency provides detailed temporal information about the search process [22].
Blink Count	BC	Number of flashes in the test	It is related to the speed of information processing. Novice learners report a higher frequency.
Blink Frequency Count	BFC	Number of blinks of all selected trials per second divided by number of selected trials	Blinks are related to information processing during exposure to a stimulus to generate the next action. Learners with faster information processing may have shorter blinks of shorter duration. However, this action may also occur when attention deficit problems are present. These results will have to be compared with those obtained in the other metrics in order to adjust the explanation of these results within the analysis of a learning pattern.
Blink Duration Total	BDT	Sum of the duration of all blinks of the selected trials divided by the number of trials selected	
Blink Duration Average	BDA	The sum of the duration of all blinks of all selected trials divided by the number of selected trials	
Blink Duration Maximum	BDMa	Longest duration of recorded blinks	
Blink Duration Minimum	BDMi	The shortest duration of recorded blinks	
Scan Path Length	SPL	It provides a pattern of learning behaviours for each user	The study of the behavioural patterns of learning will facilitate the teacher's orientations in relation to the way of learning. The length of the scan path provides information about reaction times in tasks with no predetermined duration.

In summary, the use of eye tracking technology for the analysis of information processing during the resolution of tasks in virtual learning environments has been shown to be a very effective tool for understanding how each student learns [23]. Moreover, recent studies conclude the need to integrate this technology in the usual learning spaces such as classrooms, although its use is still conditioned to important technical and interpretation knowledge on the part of the teacher [24]. Therefore, more research studies are needed to find out which of the presentation conditions of a learning task are more or less effective in learning depending on the characteristics of each learner (age, previous knowledge, learning style, etc.) [25].

1.2. Use of Data Mining and Pattern Mining Techniques in the Interpretation of the Results Obtained with the Eye Tracking Methodology

There are many studies on the application of eye tracking technology that address the model of understanding the results obtained in the different metrics. To do so, they analyse the differences in results between experts vs. novices. Experts use additional information and solve a task faster and in less time. These studies also analyse behavioural patterns by comparing the type of participant, the type of pattern and the efficiency in solving the task. Cluster analysis metrics on frequency, time and effort are used to perform these analyses. Experts vs. novices use the additional information, e.g., colour and layout, in order to use the most efficient way of navigating the platform [11]. Additionally, experts seem to be faster, meaning they will solve tasks faster and more accurately. However, novice students seem to have a greater ability to understand the tasks [13]. Nevertheless, a comparative analysis of the performance of either the same learner in their learning process or between different types of learners (e.g., novices vs. experts) [26,27] requires the use of different data mining techniques [21,28]. These can be supervised learning (related to prediction or classification) [21] or unsupervised learning (related to the use of clustering techniques) [29]. Such techniques applied to the analysis of user learning have been called educational data mining (EDM) techniques [30]. Likewise, especially in the field of analysing student behaviour during task solving, the importance of using pattern analysis techniques within what has been called educational process mining (EPM) [31] stands out. EPM is a process that focuses on detecting among the possible variables of a study those that have a greater predictive capacity. These variables may be unknown or partially known. In short, EPM thus focuses on assuming a different type of data called events. Each event belongs to a single instance of the process, and these events are related to the activities. EPM is interested in end-to-end processes and not in local patterns [31]. The general objective of instance selection techniques (e.g., prototype selection) is to "try to eliminate from the training set those instances that are misclassified and, at the same time, to reduce possible overlaps between regions of different classes, i.e., their main goal is to achieve compact and homogeneous groupings" [32] (p. 2). These analyses would belong to the supervised machine learning techniques of classification and also to the statistical techniques related to knowing which possible independent variable or variables are the ones that have a significant weight on the dependent variable or variables. The common aim of these techniques would be the elimination of noise [33], which in experimental psychology would be related to the development of pre-experimental descriptive studies [34].

In summary, feature selection techniques are a very important part of machine learning and very useful in the field of education, as they will make it possible to eliminate those attributes that contribute little or nothing to the understanding of the results in an educational learning process. Knowledge of these aspects will be essential for the proposal of new research and in the design of educational programmes [8,35]. In brief, the use of sequence mining techniques [36] and the selection of instances used in studies on the analysis of the metacognitive strategies used during task resolution processes will be very useful for the development of personalised educational intervention proposals.

1.3. Application of the Use of Eye Tracking Technology

The cognitive procedure in the process of visual tracking of images, texts or situations in natural contexts is based on the stimulus–processing–response structure. Information enters via the visual pathway (retina-fovea) and is processed at the level of the subcortical and cortical regions within the central nervous system. This processing results in a sensory stimulation response. Specifically, saccades are a form of sensory-to-motor transformation from a stimulus that has been found to be significant. Saccadic eye movements are used to redirect the fovea from one point of interest to another. Fixation is also used to keep the fovea aligned on the target during subsequent analysis of the stimulus. This alternative saccade–fixation behaviour is repeated several hundred thousand times a day and is essential in complex behaviours such as reading and driving. Saccades can be triggered by the appearance of a visual stimulus that is motivating to the subject or initiated voluntarily by the person's interest in an object. Saccades can be suppressed during periods of visual fixation. In these situations, the brain must inhibit the automatic saccade response [37]. Eye tracking technology collects, among others, metrics related to fixations, saccades and blinks. This technology is also used in studies on information processing in certain learning processes (reading, driving machines or vehicles, marketing, etc.) in people without impairments [38–45] or in groups with different impairments such as attention deficit hyperactivity disorder or autism spectrum disorder [45]. In these cases, the objective is to analyse the users' difficulties in order to make proposals for therapeutic intervention. This technology is also being used as an accident avoidance strategy [43]. Similarly, this technology can be used to study the behavioural patterns of subjects and to analyse the differences or similarities between different groups [44–46]. Eye tracking is also currently being used to test the human–machine interface based on monitoring the control of smart homes through the Internet of Things [47]. In addition, this technology is being incorporated into mobile devices. This will soon facilitate its use by users in natural contexts [48]. Similarly, eye tracking technology is being incorporated into virtual and augmented reality scenarios as the software for registration is included within the glasses [49–51]. Similarly, eye tracking technology is being incorporated into the control of industrial robots [52,53]. Finally, systems are being implemented to improve the calibration and tracking of gaze tracking for users who were previously unable to use it, due to various neurological conditions (stroke paralysis or amputations, spinal cord injuries, Parkinson's disease, multiple sclerosis, muscular dystrophy, etc.) [53]. However, these applications are still very novel and require very specific knowledge of application, and processing and interpretation of the metrics. However, progress is being made in this aspect with the implementation of interpretation algorithms in software, such as machine learning techniques for supervised learning of classification, including algorithms such as *k*-nn and random forests [54].

Based on the above theoretical foundation, a study was carried out on the analysis of the behaviour of novice vs. expert learners during the performance of a self-regulated learning task. This task was carried out in a virtual environment with multimedia resources (self-regulated video) and was monitored using eye tracking technology.

In this study, two types of analysis were used. On the one hand, statistical techniques based on analysis of covariance (ANCOVA) were used on two fixed effects factors which have been shown to be relevant in the research literature, the type of participant (novice vs. expert) and age (in this study, over 50 years old vs. under 50 years old). In addition, whether the participant is a student vs. a teacher was considered as a covariate on the dependent variables learning outcomes in solving a crossword puzzle task and eye tracking metrics (fixations, saccades, blinks and scan path length).

The hypotheses were as follows:

RQ1. Will there be significant differences in the results of solving a crossword puzzle depending on whether the participants are novices vs. experts, taking into account the covariate student vs. teacher?

RQ2. Will there be significant differences in fixations, saccades, blinks and scan path length metrics depending on the age of the participant (over 50 vs. under 50), taking into account the covariate student vs. teacher?

RQ3. Will there be significant differences in the metrics of fixations, saccades, blinks and scan path length depending on whether the participants are novices vs. experts, taking into account the covariate student vs. teacher?

On the other hand, this study applied a data analysis procedure using different supervised learning algorithms for feature selection. The objective was to find out the most significant attributes with respect to all the variables (characteristics of the participants and metrics obtained with eye tracking technology).

2. Materials and Methods

2.1. Participants

A disaggregated description of the sample with respect to the variables age, gender and type of participant (prior knowledge vs. no prior knowledge; teacher vs. student) can be found in Table 2.

Table 2. Descriptive statistics of the sample.

Participant Type	N	With Prior Knowledge (n = 17)							Without Prior Knowledge (n = 21)						
		N	n	Men		n	Woman		N	n	Men		n	Woman	
				M_{age}	SD_{age}		M_{age}	SD_{age}			M_{age}	SD_{age}		M_{age}	SD_{age}
Students	14	9	5	49.00	23.40	4	45.25	23.47	5	4	30.25	7.93	1	22.00	-
Teachers	24	8	5	47.40	8.62	3	42.67	11.85	16	9	43.00	11.79	7	52.29	4.79

Note. M_{age} = mean age; SD_{age} = standard deviation age.

2.2. Instruments

The following resources were used:

1. Eye tracking equipment iView XTM, SMI Experimenter Center 3.0 and SMI BeGazeTM. These tools record eye movements, their coordinates and the pupillary diameters of each eye. In this study, 60 Hz, static scan path metrics (fixations, saccades, blinks and scan path) were used. In addition, participants viewed the performance of the learning task on a monitor with a resolution of 1680 × 1050.

2. Ad hoc questionnaire on the characteristics of each participant (age, gender, level of studies, branch of knowledge, current employment situation and level of previous knowledge).

The questions were related to the following:

(a) Age;
(b) Gender;
(c) Level of education;
(d) Field of knowledge;
(e) Employment status (active, retired, student);
(f) Knowledge about the origin of monasteries in Europe.

3. Ad hoc crossword puzzle on the knowledge of the information in 5 questions related to the content of the video seen and referring to the origin of monasteries in Europe.

4. Learning task that consisted of a self-regulated video through the figure and voice of an avatar that narrated the task about the origins of monasteries in Europe. The duration of the activity was 120 s.

The questions were related to the following:

(a) Monks belonging to the order of St. Benedict;
(b) Powerful Benedictine monastic centre founded in the 10th century, whose influence spread throughout Europe;
(c) Space around which the organisation of the monastery revolves;
(d) Set of rules that govern monastic life;
(e) Each of the bays or sides of a cloister.

2.3. Procedure

An authorisation was obtained from the Bioethics Committee of the University of Burgos before starting the research. In addition, convenience sampling was used to select the sample. The participants did not receive any financial compensation. They were previously informed of the objectives of the research, and a written informed consent was obtained from all of them. The first phase of the study consisted of collecting personal data and testing the level of prior knowledge. Subsequently, the calibration test was prepared for each participant, using the standard deviation of 0.1–0.9, for both eyes, with a percentage adjustment of between 86.5% and 100%. Subsequently, a test was applied, which consisted of watching a 120-s video about the characteristics of a medieval monastery. The video was designed by a specialist teacher in art history, and the voiceover was provided by a specialist in SRL. After watching the video, each participant completed a crossword puzzle with five questions about the concepts explained in the video. The evaluation sessions were always conducted by the same people: a psychologist with expertise in SRL and a computer engineer, both with experience in the operation of eye tracking technology. Figure 1 shows an image of the calibration procedure and Figure 2 shows the viewing of the video and the completion of the crossword puzzle.

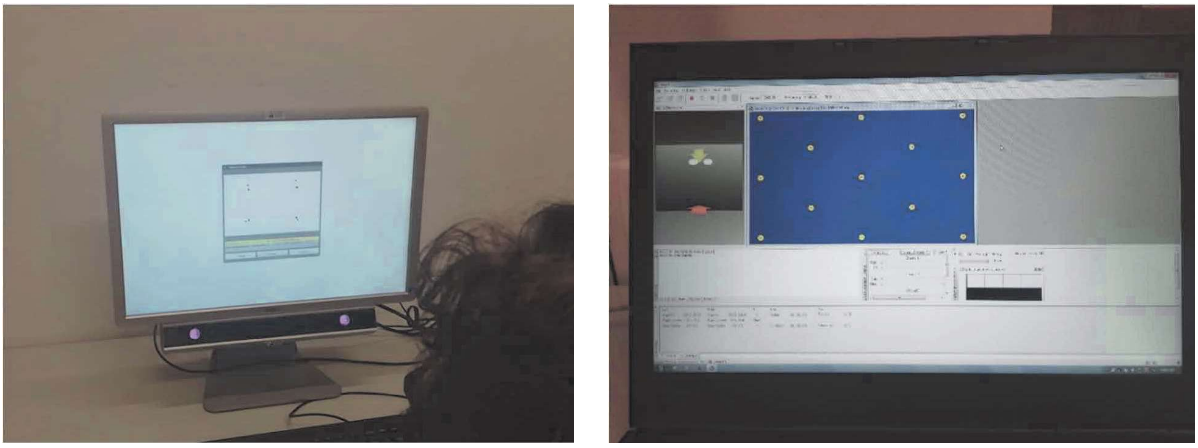


Figure 1. Calibration with eye tracking.

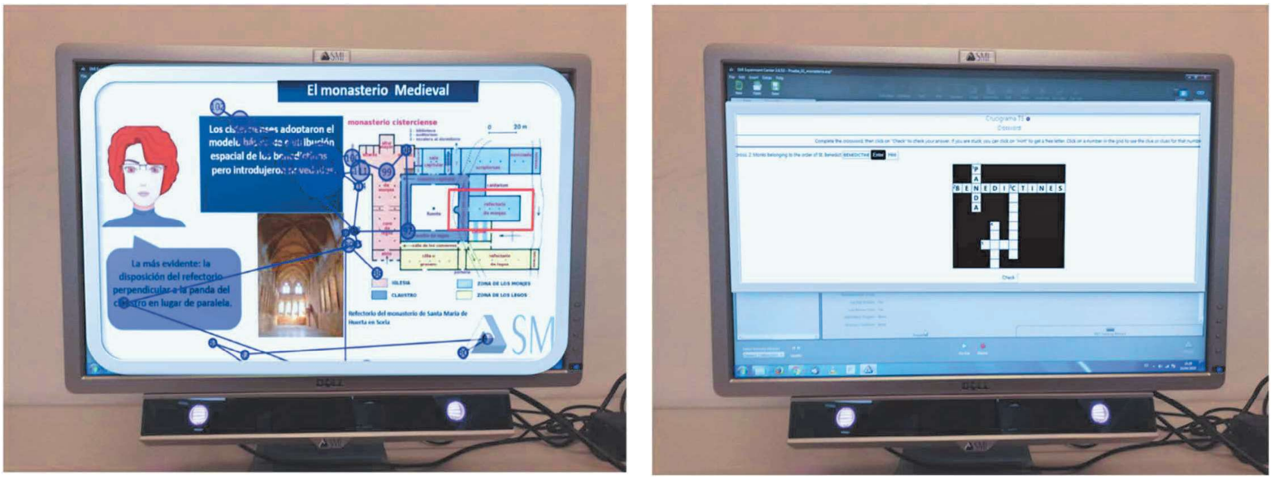


Figure 2. Watching the video and carrying out the crossword puzzle. Note. The circles on the image on the right indicate each point of fixation of the learner on each element in the visual tracking sequence of the image.

2.4. Data Analysis

2.4.1. Statistical Study

A study was conducted using three-factor fixed effects analysis of variance (ANOVA) statistical techniques (type of participant, i.e., student vs. teacher, age (over 50 years old vs. under 50 years old) and knowledge (expert vs. novices)) and eta squared effect value analysis (η^2). Analyses were performed with the SPSS v.24 statistical package [55].

A 2 × 2 × 2 factorial design (experts vs. non-experts, students vs. teachers, age (over 50 years old vs. under 50 years old)) was used [34]. The independent variables were type of participant (experts vs. novice), age (over 50 years old vs. under 50 years old) and participant type (students vs. teachers). The dependent variables were as follows:

- Solving crossword puzzle results;
- Fixations (fixation count, fixation frequency count, fixation duration total, fixation duration average, fixation duration maximum, fixation duration minimum, fixation dispersion total, fixation dispersion average, fixation dispersion maximum, fixation dispersion minimum);
- Saccades (saccade count, saccade frequency count, saccade duration total, saccade duration average, saccade duration maximum, saccade duration minimum, saccade amplitude total, saccade amplitude average, saccade amplitude maximum, saccade amplitude minimum, saccade velocity total, saccade velocity average, saccade velocity maximum, saccade velocity minimum, saccade latency average);
- Blinks (blink count, blink frequency count, blink duration total, blink duration average, blink duration maximum, blink duration minimum) and scan path length.

These metrics are related to the analysis of the cognitive procedure during visual tracking. This procedure is based on the stimulus–processing–response structure. Information enters via the visual pathway (retina-fovea) and is processed at the level of subcortical and cortical regions within the central nervous system. This processing results in a sensory stimulation response. Specifically, saccades constitute a form of sensory-to-motor transformation in response to a stimulus that has been found to be significant and a sensorimotor control of the processing. Saccadic eye movements are used to redirect the fovea from one point of interest to another. Likewise, fixation is used to keep the fovea aligned on the target during subsequent image analysis. This alternating saccade–fixation behaviour is repeated several hundred thousand times a day in humans and is central to complex behaviours such as reading. Saccades can be triggered by the appearance of a visual stimulus that is motivating to the subject or initiated voluntarily by the person's interest in a particular object. Saccades can be suppressed during periods of visual fixation, in which case the brain must inhibit the automatic saccade response [37]. The whole process is summarised in Figure 3. In addition, a video (https://youtu.be/DlRK21afGgo access on 28 June 2021) on the process of performing the task applied in this study can be consulted. In this video, the fixation and saccade points can be seen.

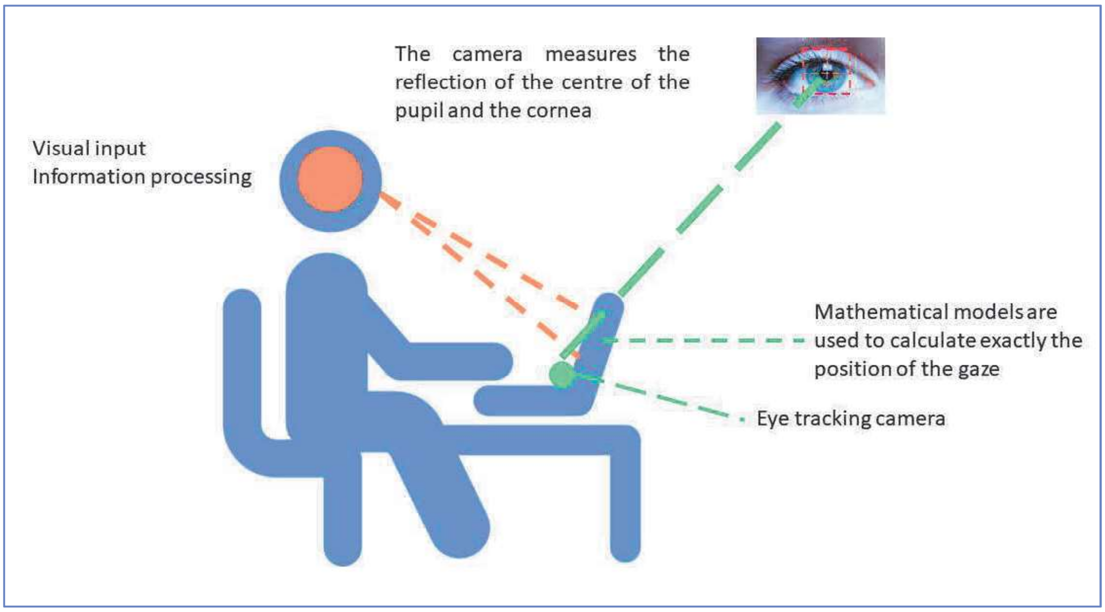


Figure 3. Visual tracking process during the resolution of a task.

2.4.2. Study Using Machine Learning Techniques

As stated in the introduction, machine learning techniques can be divided into supervised learning techniques, which in turn can be subdivided into classification and prediction techniques [21], and unsupervised learning, which refers to the use of clustering techniques [29]. Specifically, supervised learning techniques of pattern analysis are used for human behavioural analysis. These would fall within the supervised learning techniques of clustering [31,32,36]. Concretely, in this study, we used supervised automatic learning techniques for classification (the gain ratio, symmetrical uncertainty and chi-square algorithms were applied) and unsupervised clustering (the *k*-means ++, fuzzy *k*-means and DBSCAN algorithms were applied). The analyses were performed with the R programming language [56].

In the study with machine learning techniques, a descriptive correlational design was applied [34]. A supervised learning analysis of classification and non-supervised clustering was applied on all features.

3. Results

3.1. Statistical Study

3.1.1. Previous Analyses

Before starting the testing of the hypotheses, it was checked whether the sample followed a normal distribution, for which a study was conducted on the values of skewness (values below $|2.00|$ are considered accepted values, and a value of skewness = -0.22 was found) and kurtosis (values below $|8.00|$ are considered accepted values, and a value of kurtosis = -2.06 was found). Therefore, the results indicate that the distribution follows the assumptions of normality, which is why parametric statistics were used to test the hypotheses.

3.1.2. Hypothesis Testing Analysis

To test RQ1, a one-factor fixed effects ANCOVA was applied for the participant type "expert vs. novice" considering the covariate (participant type "student vs. teacher") with respect to the dependent variable crossword result. No significant differences were found, but a mean effect value was found (F = 1.91, $p = 0.40$, $\eta^2 = 0.66$). Additionally, no effect of the covariate was found (F = 0.03, $p = 0.90$, $\eta^2 = 0.03$), and in this case, the effect value was low.

To test RQ2, a one-factor fixed effects ANCOVA (participant type "over 50 vs. under 50") was applied considering the covariate (participant type "student vs. teacher"). No significant differences were found in the metrics of fixations, saccades, blinks and scan path length. A covariate effect was only found in the metrics of saccade amplitude minimum (F = 5.19, $p = 0.03$, $\eta^2 = 0.13$) and saccade velocity minimum (F = 5.18, $p = 0.03$, $\eta^2 = 0.13$), in both cases with a low effect value. All results can be found in Table A1 in Appendix A.

Regarding test RQ3, a one-factor fixed effects ANCOVA (participant type "novice vs. expert") was applied considering the covariate (participant type "student vs. teacher"). No significant differences were found in the metrics of fixations, saccades, blinks and scan path length. The effect of the covariate was only found in the metrics of saccade amplitude minimum (F = 6.90, $p = 0.01$, $\eta^2 = 0.16$) and saccade velocity minimum (F = 7.67, $p = 0.01$, $\eta^2 = 0.18$), and in both cases, the effect value was medium. All results can be found in Table A2 in Appendix A.

3.2. Study with Supervised Learning Machine Learning Techniques: Feature Selection

A feature selection analysis was performed with the R programming package mclust, selecting from all possible variables those that received a positive ranking. The gain ratio, symmetrical uncertainty and chi-square algorithms were used for feature selection. Table 3 shows the best values found with each of them for feature selection.

Table 3. Best performing features in the gain ratio, symmetrical uncertainty and chi-square feature selection algorithms.

Features	Gain Ratio	Symmetrical Uncertainty	Chi-Square
Previous Knowledge	0.199	0.199	0.453
Group Type	0.238	0.171	0.421
Employment Status	0.238	0.171	0.421
Gender	0.108	0.067	0.372
Level Degree	0.100	0.082	0.263
Knowledge Branch	0.084	0.057	0.251

(a) The gain ratio is a feature selection method that belongs to the filtering methods. It relies on entropy to assign weights to discrete attributes based on their correlation between the attribute and a target variable (in this study, the results in solving the crossword puzzle). The gain ratio focuses on the information gain metric [57], traditionally used to choose the attribute at a node of a decision tree with the ID3 method. This is the one that generates a partition in which the examples are distributed less randomly among the classes. This method was improved by Quinlan in 1993 [58], as he detected that the information gain was calculated with an unfair favouritism towards attributes with many results. To correct this, he added a value correction based on standardisation by the entropy of that attribute. If Y is the variable to be predicted, then the gain ratio standardises the gain by dividing by the entropy of X. Thus, the C4.5 decision tree construction method uses this measure. From a data mining point of view, this attribute selection could be understood as the selection of attributes as best candidates for the root of a decision tree, which in this study will predict the solving crossword puzzle variable. With H being the entropy, the gain ratio equation is as follows:

$$gain\ ratio = \frac{H(Class) + H(Attribute) - H(Class, Attribute)}{H(Attribute)}$$

Figure 4 shows the correlation matrix found with the gain ratio algorithm in the selection of best features.

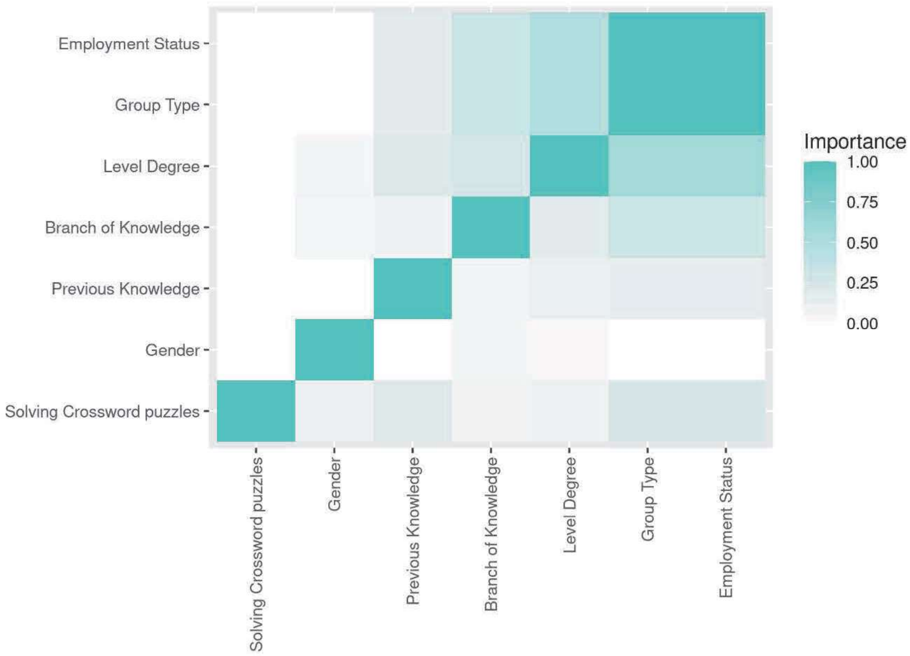


Figure 4. Relationship matrix on the selected features performed with the gain ratio algorithm.

(b) Symmetrical uncertainty is a feature selection method which, as with the gain ratio, belongs to the filter methods and is also based on entropy. Symmetrical uncertainty normalises the values in the range [0, 1]. It also normalises the gain by dividing by the sum of the attribute and class entropies, where H is the entropy.

$$symmetrical\ uncertainty = 2 \times \frac{H(Class) + H(Attribute) - H(Class,\ Attribute)}{H(Attribute) + H(Class)}$$

Figure 5 shows the correlation matrix found with the symmetrical uncertainty algorithm on the best features.

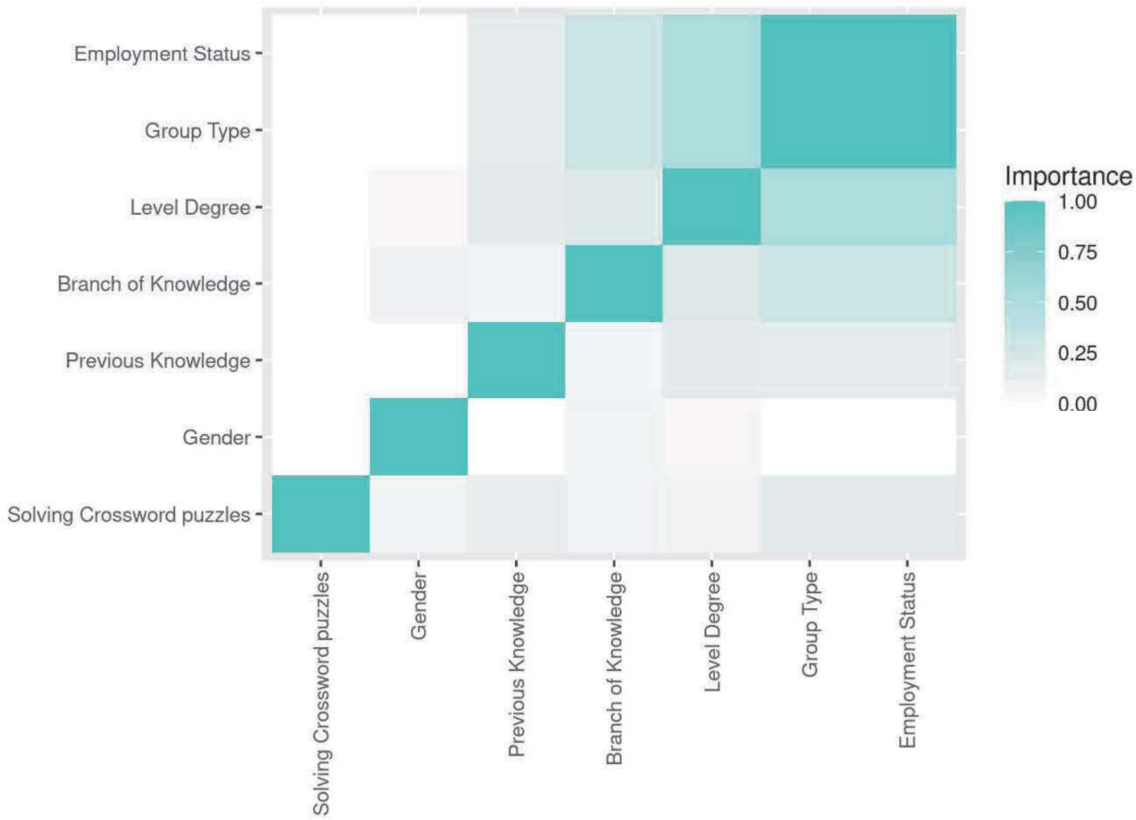


Figure 5. Relationship matrix on the selected features performed with the symmetrical uncertainty algorithm.

(c) Chi-square is a feature selection algorithm that belongs to the filter type and tries to obtain the weights of each feature by using the chi-square test (in case the features are not nominal, it discretises them). The selection result is the same as Cramer's V coefficient. The chi-square equation is as follows:

$$\chi^2 = \sum_{i=1}^{k} \frac{(Oi + Ei)^2}{Ei}$$

where Oi is the observed or empirical absolute frequency and Ei is the expected frequency.

Figure 6 shows the correlation matrix found with chi-square (χ^2) [59].

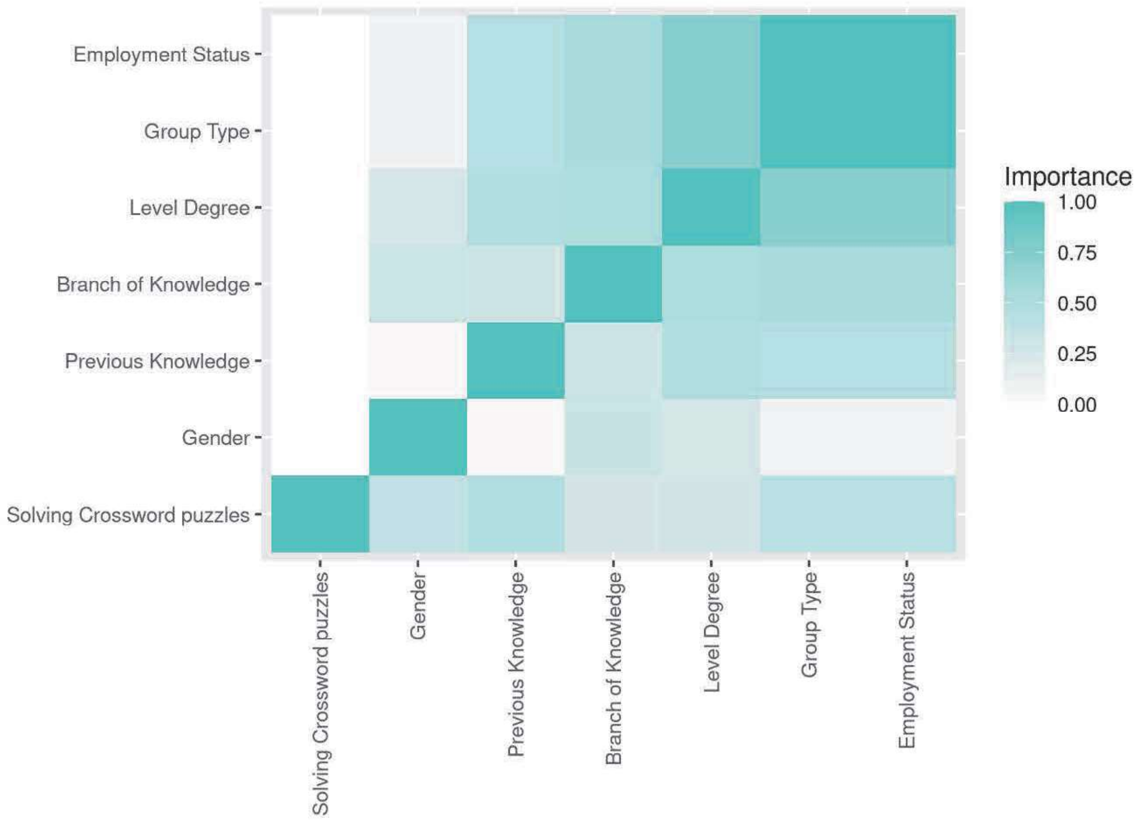


Figure 6. Relationship matrix on the selected characteristics performed with the chi-square algorithm.

3.3. Study with Unsupervised Learning Machine Learning Techniques: Clustering

Finally, cluster detection was performed on the data with unsupervised learning techniques, ignoring the solving crossword puzzles parameter in order to detect patterns in the instances. Nominal variables were transformed into dummy variables in such a way that a variable with n possible different values was divided into n-1 new binary variables, meaning that each of them indicated belonging to one of the previous values. The data were normalised by normalising the mean of the attributes to 0 and the standard deviation to 1. The following clustering algorithms were used:

(a) *k*-means++ is an algorithm for choosing the initial values of the centroids for the *k*-means clustering algorithm. It was proposed in 2007 by Arthur and Vassilvitskii [60] as an approximation algorithm for solving the NP-hard *k*-means problem. That is, a way to avoid the sometimes poor clustering encountered by the standard *k*-means clustering algorithm.

$$D^2(\mu_0) \leq 2D^2(\mu_i) + 2||\mu_i - \mu_0||^2$$

where μ_0 is the initial point selected and D is the distance between point μ_i and the nearest centre of the cluster. Once the centroids are chosen, the process is like the classical *k*-means.

(b) The fuzzy *k*-means algorithm combines the methods based on the optimisation of the objective function with those of fuzzy logic [61,62]. This algorithm performs cluster formation through a soft partitioning of the data. That is, a piece of data would not belong exclusively to a single group but could have different degrees of belonging to several groups. This procedure calculates initial means (m_1, m_2, ..., m_k) to find the degree of membership of data in a cluster. As long as there are no changes in these means, the degree of membership of each data item x_j in cluster i is calculated.

$$u(j,\ i) = \frac{e^{-(||x_j - m_i||^2)}}{\sum_j e^{-(||x_j - m_i||^2)}}$$

where m_i is the fuzzy mean of all the examples in cluster i.

$$m_i = \frac{\sum_j^i u(j,i)^2 x_j}{\sum_j u(j,i)^2}$$

(c) DBSCAN (density-based spatial clustering of applications with noise) [63] is understood as an algorithm that identifies clusters describing regions with a high density of observations and regions of low density. DBSCAN avoids the problem that other clustering algorithms have by following the idea that, for an observation to be part of a cluster, there must be a minimum number of neighbouring observations (minPts) within a proximity radius (epsilon) and that clusters are separated by empty regions or regions with few observations.

As all remaining variables were nominal after feature selection, after pre-processing the data, only clustering with binary variables was used, which complicated the processing of the k-means++ algorithm by placing the centroids at different locations in the space when the number of centroids was bigger than three. For this reason, the parameter value k in the k-means++ and fuzzy k-means algorithms was equal to 3.

The value of the DBSCAN algorithm parameters was 5 for the minPts variable as it is the default value in the library [64]. To choose the epsilon value, the elbow method was applied. Figure 7 shows the average distance of each point to its nearest neighbouring minPts, and the value 2.97 was chosen for this parameter.

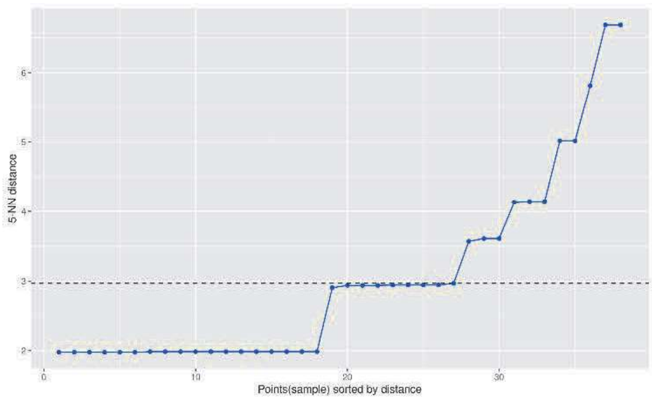


Figure 7. Elbow method in the DBSCAN algorithm.

The visualisation of the clustering results can be seen in Figure 8, which shows the data after applying dimensionality reduction with the principal component analysis (PCA) method. The clusters selected by the k-means++ and fuzzy k-means algorithms are identical, while DBSCAN only found two clusters, leaving instances out of them. These instances labelled as noise in this study are assigned to an additional cluster.

Finally, it has to be considered that when applying an unsupervised learning method, such as clustering, there is no objective variable to evaluate the goodness of the distribution of instances in clusters. However, the goodness of clustering can be tested using the adjusted Rand index (ARI), in order to compare how similar the clustering algorithms are to each other. Thus, if many algorithms perform similar partitions, the conclusion will be consistent [65]. That is, if a pair of instances is in the same cluster in both partitions, this fact will represent similarity between these partitions. In the opposite case, where a pair of instances is in the same cluster in one partition and in different clusters in the other category, it will represent a difference. With n being the number of instances, a being the number of pairs of instances grouped in the same cluster in both partitions and b being the number of pairs of instances grouped in different clusters in different partitions, the Rand index (without adjustment and correction) would be as follows:

$$a = |S_{eq}|,\ where\ S_{eq} = \{(o_i,\ o_j)|o_i,\ o_j \in X_k,\ o_i,\ o_j \in Y_l,\ \}$$
$$b = |S_{eq}|,\ where\ S_{eq} = \{(o_i,\ o_j)|o_i \in X_{k1},\ o_j \in X_{k2},\ o_i \in X_{l1},\ o_j \in Y_{l2},\ \}$$
$$Rand\ index = \frac{a+b}{\binom{n}{2}}$$

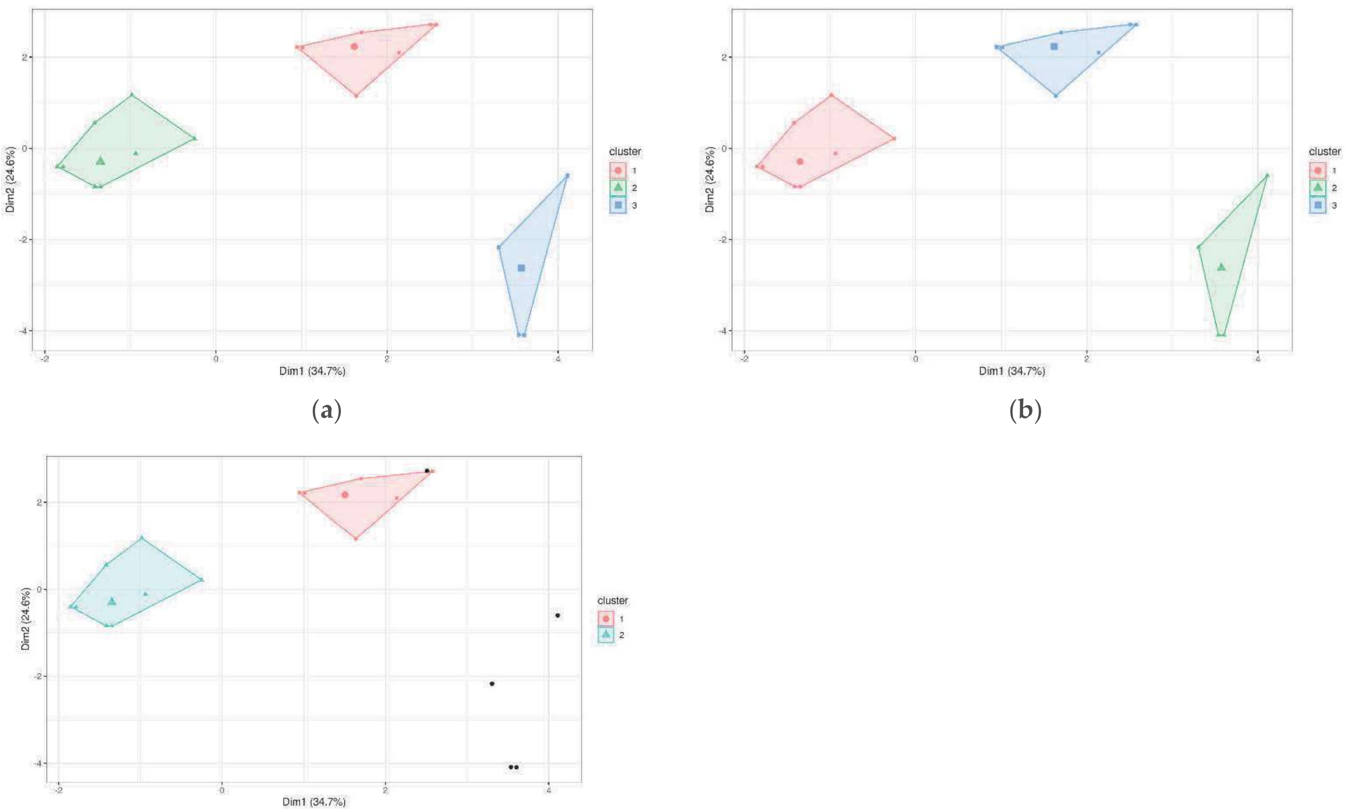
A correction is made to the original intuition of the Rand index, since the expected similarity between two partitions established with random models can have pairs of instances that coincide, and this fact would cause the Rand index to never be 0. To make the correction, the adjusted Rand index algorithm, ARI, was applied, in which negative values can be found if the similarity is less than expected, being equal to

$$Adjusted\ rand\ index = \frac{Index - Expected\ Index}{Maximun\ Index - Expected\ Index}$$

The applied ARI formula is therefore

$$ARI = \frac{\sum_{ij}\binom{n_{ij}}{2} - \left[\sum_i \binom{a_i}{2} \sum_j \binom{b_j}{2}\right] \Big/ \binom{n}{2}}{\frac{1}{2}\left[\sum_i \binom{a_i}{2} \sum_j \binom{b_j}{2}\right] \Big/ \binom{n}{2}}$$

where if $X = \{X_1, X_2, \ldots, X_r\}$ and $Y = \{Y_1, Y_2, \ldots, Y_s\}$, then $n_{ij} = Xi \cap Yj$, $ai = \sum_{jnij}$ and $b_i = \sum_{inij}$.



(a) (b) (c)

Figure 8. (**a**) Clustering with the *k*-means ++ algorithm; (**b**) clustering with the fuzzy means algorithm; (**c**) clustering with the DBSCAN algorithm.

Thus, the ARI can have a value between −1 and 1, where 1 indicates that the two data clusters match exactly in every pair of points, 0 is the expected value for randomly created clusters and −1 is the worst fit. The results indicate that the algorithms that provide the best fit are *k*-means ++ and fuzzy *k*-means (ARI = 1), *k*-means ++ and DBSCAN (ARI = 0.96) and fuzzy *k*-means and DBSCAN (ARI = 0.9), where the higher the intensity, the higher the relationship. It can therefore be concluded that the degree of fit between the algorithms applied in this study is good for all possible associations (show Figure 9).

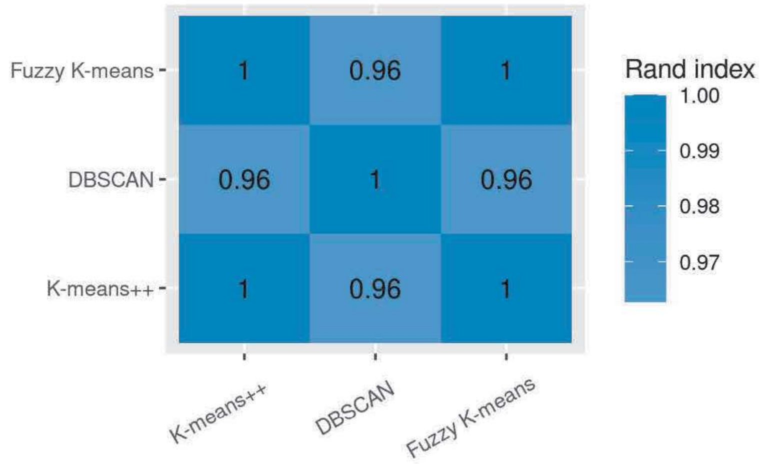


Figure 9. Adjusted Rand index (ARI).

4. Discussion

Regarding the results found in the RQ1 check, it was not confirmed that participants with prior knowledge performed better on the crossword puzzle solving test than non-experts. In line with studies by Eberhard et al. [2], Takacs and Bus [4] and Verhallen and Bus [5], this may be explained by the fact that the task was presented in a video that included self-regulated speech. This technique has been shown to be very effective in mitigating the differences between novice vs. experienced learners [12–14]. However, although no significant differences were found with respect to the independent variable, a mean effect value was found. This suggests that the participant type variable "novice vs. expert" is an important variable in task resolution processes. However, in this study, this effect may have been mitigated by the way the task was presented (self-regulated procedure). This result coincides with the findings of studies that conclude that the lack of prior knowledge in novice learners can be compensated by the proposal of self-regulated multi-measure tasks [12–15,35,36]. The explanation is that self-regulated video may facilitate homogeneity in the encoding of information, attention to relevant vs. non-relevant information and in the route taken in the scan path [18,19].

Regarding RQ2, no effect of age was found on the metrics of fixations, saccades, blinks and scan path length. This may be explained by the way the task was presented (self-regulated video), or by the participants' prior knowledge. In this line, research [8] supports that prior knowledge compensates for the effects of age on cognitive functioning, for example, on long-term memory processes or reaction times. In addition, it has been found that the covariate participant type "student vs. teacher" does weigh on task performance. Specifically, differences were found in the saccade amplitude minimum and saccade velocity minimum parameters. These data can be related to the findings of studies indicating that age effects can be mitigated by learners' prior knowledge of the task [8] and also by self-regulated presentation of the task [18,19]. In fact, the significant differences found in the covariate focused on saccade amplitude and minimum saccade velocity, which is consistent with studies that found differences in saccade type depending on the phase of information encoding the learner was at [18,19]. This result is important for future research proposals. The reason is that the way students vs. teachers process information might be influencing the way they learn. For example, teachers might develop more systematic processing that would compensate for their lack of knowledge in a task. Alternatively, younger students might implement more effective learning, and thus processing, strategies even though they are novices [13]. These hypotheses will be explored in future studies.

Regarding RQ3, no significant differences were found in the metrics of fixations, saccades, blinks, and scan path length depending on whether the participant was a novice or an expert. This may be explained by the way the task was presented (a self-regulated video with a set time duration). However, future studies could test the results on videos that did not include self-regulation and/or that could be viewed more than once. We also found that there is an effect of the covariate participant type "student vs. teacher" on the saccade amplitude minimum and saccade velocity minimum parameters. As indicated in RQ2, this is an important fact to consider in future research, as the way students vs. teachers process information could be influencing the type of information processing. Similarly, future studies could test whether the form of task presentation (self-regulated vs. non-self-regulated; timed vs. untimed, etc.) could be influencing the form of processing (fixations, saccades, blinks, scan path length). Similarly, processing patterns could be found for different participant types (novice vs. expert, with different age intervals, etc.), and the types of patrons could be tested according to the type of participant.

According to the analysis performed with supervised learning methods of feature selection, it was found that the different algorithms applied (gain ratio, symmetrical uncertainty, chi-square) provided valuable information regarding the most significant attributes in the study. In this case, the following attributes were considered as important: previous knowledge, group type, employment status, gender, level degree and knowledge branch. This result is very interesting for future research, as it provides information on the possible effects of characteristics that were not considered as independent variables in the statistical study (employment status, gender, level degree and knowledge branch).

Regarding the study with unsupervised learning techniques (clustering), it allowed us to know the grouping, i.e., the similar interaction patterns of the participants in the selected characteristics. The three algorithms applied had a good ARI. This result is important for future studies, as a learning style profile can be extracted for each group and its relationship with the outcome of the learning tasks and with the reaction times for the execution of the tasks can be checked.

5. Conclusions

The use of the eye tracking technique provides evidence on the processing of information in different types of participants during the resolution of different tasks [9–11]. This fact facilitates research in behavioural sciences [37]. Working with this technology opens up many fields of research applied to numerous environments (learning to read and write, logical-mathematical reasoning, physics, driving vehicles, driving dangerous machines, marketing, etc.) [38–42]. It can also be used to find out how people with different learning disabilities [45] (ADHD, ASD, etc.) learn. Therefore, it could improve their learning style and make proposals for personalised intervention according to the needs observed in each of them. In addition, this technology can be used to improve driving practices and accident prevention with regard to the handling of dangerous machinery. This training is being carried out in virtual and/or augmented reality scenarios [49–51] that apply eye tracking technology. All these possibilities open an important field to be addressed in future research.

Another relevant aspect to take into account is the way tasks are presented. This study has shown that the use of self-regulated tasks facilitates the processing of information and homogenises learning responses between novice and expert learners [12–15,35,36]. Therefore, in future studies, we will study participants' processing in different types of tasks (self-regulated designs with avatars, zooming in on the most relevant information, etc.). Likewise, the results will be tested in different educational stages (early childhood education, primary education, secondary education, university education and non-formal education) and in different subjects (experimental vs. non-experimental).

Subsequently, this study has shown that the use of different automatic learning techniques such as feature selection facilitates the knowledge of attributes that may be more significant for the research. This functionality is very useful in research that works with a large volume of features or instances. Moreover, if this technique is combined with the use of machine learning techniques and traditional statistics, the results can provide more information, especially related to future lines of research. In fact, in this study, it has been found that some of the variables considered as independent in the statistical study were also selected as relevant features in the study that applied supervised learning techniques of instance selection (e.g., prior knowledge, type of participant (student vs. teacher)). However, the feature selection techniques have also provided clues to be taken into account in future studies on the influence of other variables (e.g., gender, employment status, level of education and field of knowledge). In this line, the use of different algorithms to test both feature selection and clustering in unsupervised learning provides the researcher with a repertoire of results whose fit can be contrasted with the ARI. This will make it possible to know the groupings among the learners and to isolate the patterns of the types of learners in order to be able to offer educational responses based on personalised learning. On the other hand, the use of statistical analysis methods makes it possible to ascertain whether the variables indicated as independent have an effect on the dependent variables. In summary, perhaps the most useful procedure is, first, to apply the techniques of supervised learning of characteristics and then, depending on the variables detected, to pose the research questions and apply the relevant statistical analyses to test them.

Finally, the results of this study must be taken with caution, as this study has a series of limitations. These are mainly related to the size of the sample, which is small, and the selection of the sample, which was conducted convenience sampling. However, it must be considered that the use of the eye tracking methodology requires a very exhaustive control of the development of tasks in laboratory spaces, an aspect that makes it difficult for the samples to be large and randomised. Another of the limiting elements of this work is that a very specific task (acquisition of the concepts of the origins of monasteries in Europe and verification of this acquisition through the resolution of a crossword puzzle) was used in a specific learning environment (history of art). For this reason, possible future studies have been indicated in the Discussion and Conclusions sections.

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Institutional Review Board Statement: The Ethics Committee of the University of Burgos approved this study No. IR27/2019.

Informed Consent Statement: Written informed consent was obtained from all participants in this study in accordance with the Declaration of Helsinki guidelines.

Data Availability Statement: The datasets generated for this study are available on request to the corresponding author.

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Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Table A1. One-factor ANCOVA with fixed effects (age over 50 vs. under 50) and covariate (student vs. teacher).

Type of Access	N	*n*	G1 *M (SD)*	*n*	G2 *M (SD)*	*df*	*F*	*p*	η^2
Independent Variable (*novel* vs. *expert*)									
Fixation Count	38	17	654.18 (138.56)	21	625.19 (189.87)	1,35	0.09	0.76	0.003
Fixation Frequency Count	38	17	3.01 (0.67)	21	2.96 (0.91)	1,35	0.09	0.76	0.003
Fixation Duration Total	38	17	166,132.18 (44,244.00)	21	152,531.78 (48,472.19)	1,35	0.49	0.49	0.01
Fixation Duration Average	38	17	255.93 (72.55)	21	254.36 (88.36)	1,35	0.004	0.95	0.000
Fixation Duration Maximum	38	17	1189.10 (484.92)	21	1286.40 (623.33)	1,35	0.42	0.52	0.01
Fixation Duration Minimum	38	17	83.21 (0.05)	21	83.21 (0.04)	1,35	0.03	0.86	0.001
Fixation Dispersion Total	38	17	47,498.23 (11,528.53)	21	46,202.81 (15,068.91)	1,35	0.01	0.93	0.000
Fixation Dispersion Average	38	17	72.50 (5.00)	21	73.58 (5.00)	1,35	0.42	0.52	0.01
Fixation Dispersion Maximum	38	17	99.98 (0.04)	21	98.89 (0.39)	1,35	0.79	0.38	0.02
Fixation Dispersion Minimum	38	17	11.54 (4.65)	21	9.94 (5.01)	1,35	0.85	0.36	0.02
Saccade Count	38	17	664.29 (136.78)	21	632.24 (195.64)	1,35	0.12	0.73	0.003
Saccade Frequency Count	38	17	3.15 (0.65)	21	3.00 (0.93)	1,35	0.12	0.73	0.003
Saccade Duration Total	38	17	32,282.09 (27,891.81)	21	31,241.80 (21,906.09)	1,35	0.03	0.86	0.001
Saccade Duration Average	38	17	59.47 (89.43)	21	52.58 (44.21)	1,35	0.23	0.63	0.02
Saccade Duration Maximum	38	17	629.38 (1332.76)	21	467.00 (414.22)	1,35	0.49	0.49	0.01
Saccade Duration Minimum	38	17	16.57 (0.05)	21	16.49 (0.30)	1,35	2.00	0.17	0.05
Saccade Amplitude Total	38	17	4825.23 (6815.38)	21	4740.95 (4780.52)	1,35	0.02	0.88	0.001
Saccade Amplitude Average	38	17	10.74 (25.55)	21	8.69 (10.82)	1,35	0.26	0.61	0.02
Saccade Amplitude Maximum	38	17	156.15 (300.65)	21	119.67 (96.25)	1,35	0.47	0.50	0.013
Saccade Amplitude Minimum	38	17	0.03 (0.05)	21	0.05 (0.07)	1,35	0.35	0.56	0.010
Saccade Velocity Total	38	17	61,828.35 (17,396.33)	21	66,554.31 (26,550.69)	1,35	0.50	0.49	0.014
Saccade Velocity Average	38	17	96.85 (36.43)	21	113.01 (45.91)	1,35	0.95	0.34	0.03
Saccade Velocity Maximum	38	17	878.00 (190.65)	21	844.58 (173.95)	1,35	0.25	0.62	0.01
Saccade Velocity Minimum	38	17	2.81 (1.43)	21	3.62 (2.47)	1,35	0.75	0.39	0.02
Saccade Latency Average	38	17	279.93 (64.36)	21	295.73 (106.93)	1,35	0.12	0.73	0.003
Blink Count	38	17	33.12 (25.59)	21	45.00 (37.00)	1,35	1.14	0.29	0.03
Blink Frequency Count	38	17	0.15 (0.12)	21	0.21 (0.18)	1,35	1.14	0.29	0.03
Blink Duration Total	38	17	6777.12 (9174.98)	21	20,619.05 (41,403.88)	1,35	1.36	0.25	0.04
Blink Duration Average	38	17	202.48 (244.52)	21	545.61 (1352.20)	1,35	0.77	0.39	0.02
Blink Duration Maximum	38	17	898.75 (2087.86)	21	5951.36 (19,080.82)	1,35	0.88	0.36	0.02
Blink Duration Minimum	38	17	85.19 (5.57)	21	84.80 (5.05)	1,35	0.07	0.79	0.002
Scan Path Length	38	17	122,506.94 (21157.24)	21	117,620.71 (36,042.24)	1,35	0.16	0.69	0.01

Table A1. *Cont.*

Type of Access	N	*n*	G1 *M (SD)*	*n*	G2 *M (SD)*	*df*	*F*	*p*	η^2
Covariable (*type of participant student* vs. *professor*)									
Fixation Count	38	17		21		1,35	1.61	0.21	0.04
Fixation Frequency Count	38	17		21		1,35	1.53	0.23	0.04
Fixation Duration Total	38	17		21		1,35	1.12	0.30	0.03
Fixation Duration Average	38	17		21		1,35	0.001	0.98	0.000
Fixation Duration Maximum	38	17		21		1,35	0.60	0.44	0.02
Fixation Duration Minimum	38	17		21		1,35	0.04	0.84	0.001
Fixation Dispersion Total	38	17		21		1,35	1.36	0.25	0.04
Fixation Dispersion Average	38	17		21		1,35	0.002	0.97	0.000
Fixation Dispersion Maximum	38	17		21		1,35	0.08	0.78	0.002
Fixation Dispersion Minimum	38	17		21		1,35	0.12	0.73	0.004
Saccade Count	38	17		21		1,35	1.73	0.20	0.047
Saccade Frequency Count	38	17		21		1,35	1.65	0.21	0.045
Saccade Duration Total	38	17		21		1,35	0.11	0.74	0.003
Saccade Duration Average	38	17		21		1,35	1.05	0.31	0.03
Saccade Duration Maximum	38	17		21		1,35	1.09	0.30	0.03
Saccade Duration Minimum	38	17		21		1,35	2.41	0.13	0.06
Saccade Amplitude Total	38	17		21		1,35	0.44	0.51	0.01
Saccade Amplitude Average	38	17		21		1,35	1.18	0.28	0.03
Saccade Amplitude Maximum	38	17		21		1,35	1.01	0.32	0.03
Saccade Amplitude Minimum	38	17		21		1,35	5.19	0.03 *	0.13
Saccade Velocity Total	38	17		21		1,35	0.28	0.60	0.01
Saccade Velocity Average	38	17		21		1,35	1.27	0.27	0.04
Saccade Velocity Maximum	38	17		21		1,35	0.08	0.77	0.002
Saccade Velocity Minimum	38	17		21		1,35	5.18	0.03 *	0.13
Saccade Latency Average	38	17		21		1,35	1.19	0.28	0.03
Blink Count	38	17		21		1,35	0.02	0.81	0.001
Blink Frequency Count	38	17		21		1,35	0.000	0.98	0.000
Blink Duration Total	38	17		21		1,35	0.93	0.34	0.03
Blink Duration Average	38	17		21		1,35	0.58	0.45	0.02
Blink Duration Maximum	38	17		21		1,35	0.53	0.47	0.02
Blink Duration Minimum	38	17		21		1,35	0.09	0.77	0.003
Scan Path Length	38	17		21		1,35	0.21	0.65	0.01

Note. G1 = participants younger than 50 years; G2 = participants older than 50 years; *M* = mean; *SD* = standard deviation; *df* = degrees of freedom; η^2 = eta squared effect value; * $p < 0.05$.

Table A2. One-factor ANCOVA with fixed effects (age over 50 vs. under 50) and covariate (student vs. teacher).

Type of Access	N	*n*	G1 *M (SD)*	*n*	G2 *M (SD)*	*df*	*F*	*p*	η^2
Independent Variable (*novel* vs. *expert*)									
Fixation Count	38	25	628.92 (183.40)	13	655.92 (136.21)	1,35	0.55	0.46	0.02
Fixation Frequency Count	38	25	2.98 (0.88)	13	3.10 (0.65)	1,35	0.51	0.48	0.01
Fixation Duration Total	38	25	152,469.04 (54,256.14)	13	170,437.56 (23,520.29)	1,35	1.98	0.17	0.05
Fixation Duration Average	38	25	243.64 (69.26)	13	277.03 (98.19)	1,35	1.49	0.23	0.04
Fixation Duration Maximum	38	25	1184.55 (512.27)	13	1355.00 (650.35)	1,35	1.06	0.31	0.03
Fixation Duration Minimum	38	25	83.22 (0.06)	13	83.20 (0.00)	1,35	1.16	0.29	0.03
Fixation Dispersion Total	38	25	46,170.27 (14,279.23)	13	47,959.40 (12,120.32)	1,35	0.39	0.54	0.01

Table A2. *Cont.*

Type of Access	N	*n*	G1 *M (SD)*	*n*	G2 *M (SD)*	*df*	*F*	*p*	η^2
Fixation Dispersion Average	38	25	73.19 (4.65)	13	72.89 (5.72)	1,35	0.04	0.84	0.001
Fixation Dispersion Maximum	38	25	99.90 (0.36)	13	99.99 (0.03)	1,35	1.03	0.32	0.03
Fixation Dispersion Minimum	38	25	11.02 (4.59)	13	9.95 (5.44)	1,35	0.30	0.59	0.01
Saccade Count	38	25	638.44 (186.76)	13	662.23 (139.21)	1,35	0.47	0.50	0.01
Saccade Frequency Count	38	25	3.03 (0.89)	13	3.12 (0.67)	1,35	0.36	0.55	0.01
Saccade Duration Total	38	25	35,070.90 (28,103.57)	13	25,238.52 (13,761.84)	1,35	1.57	0.22	0.04
Saccade Duration Average	38	25	65.17 (81.24)	13	37.38 (14.49)	1,35	2.06	0.16	0.06
Saccade Duration Maximum	38	25	633.59 (1130.76)	13	358.96 (252.82)	1,35	1.12	0.30	0.03
Saccade Duration Minimum	38	25	16.52 (0.26)	13	16.52 (0.16)	1,35	0.07	0.80	0.002
Saccade Amplitude Total	38	25	5679.51 (6777.34)	13	3046.24 (1794.51)	1,35	2.31	0.14	0.06
Saccade Amplitude Average	38	25	12.20 (22.60)	13	4.62 (2.49)	1,35	2.05	0.16	0.06
Saccade Amplitude Maximum	38	25	161.21 (254.94)	13	87.50 (56.00)	1,35	1.49	0.23	0.04
Saccade Amplitude Minimum	38	25	0.04 (0.07)	13	0.03 (0.05)	1,35	1.39	0.25	0.04
Saccade Velocity Total	38	25	66,146.90 (24,164.73)	13	61,157.70 (20,255.49)	1,35	0.31	0.58	0.01
Saccade Velocity Average	38	25	112.39 (47.64)	13	93.07 (26.12)	1,35	2.78	0.10	0.074
Saccade Velocity Maximum	38	25	882.20 (193.02)	13	815.95 (148.76)	1,35	1.02	0.32	0.03
Saccade Velocity Minimum	38	25	3.50 (2.41)	13	2.79 (1.20)	1,35	2.49	0.12	0.07
Saccade Latency Average	38	25	282.75 (76.56)	13	300.02 (113.31)	1,35	0.12	0.73	0.003
Blink Count	38	25	39.24 (29.03)	13	40.54 (39.73)	1,35	0.003	0.96	0.000
Blink Frequency Count	38	25	0.18 (0.14)	13	0.18 (0.20)	1,35	0.000	0.98	0.000
Blink Duration Total	38	25	15,683.28 (38,413.22)	13	12,009.94 (12,594.05)	1,35	0.32	0.58	0.01
Blink Duration Average	38	25	418.80 (1251.58)	13	340.78 (286.44)	1,35	0.16	0.69	0.01
Blink Duration Maximum	38	25	4263.06 (17603.20)	13	2590.82 (3294.93)	1,35	0.27	0.61	0.01
Blink Duration Minimum	38	25	85.22 (5.57)	13	84.51 (4.66)	1,35	0.20	0.66	0.01
Scan Path Length	38	25	122,693.40 (31,212.68)	13	114,255.23 (27,953.39)	1,35	0.52	0.48	0.02
Covariable (*type of participant student* vs. *professor*)									
Fixation Count	38	25		13		1,35	2.14	0.15	0.06
Fixation Frequency Count	38	25		13		1,35	2.03	0.16	0.06
Fixation Duration Total	38	25		13		1,35	2.13	0.15	0.06
Fixation Duration Average	38	25		13		1,35	0.04	0.84	0.001
Fixation Duration Maximum	38	25		13		1,35	0.74	0.40	0.02
Fixation Duration Minimum	38	25		13		1,35	0.14	0.71	0.004
Fixation Dispersion Total	38	25		13		1,35	1.69	0.20	0.05
Fixation Dispersion Average	38	25		13		1,35	0.04	0.85	0.001
Fixation Dispersion Maximum	38	25		13		1,35	0.39	0.54	0.01
Fixation Dispersion Minimum	38	25		13		1,35	0.16	0.69	0.01
Saccade Count	38	25		13		1,35	2.27	0.14	0.06
Saccade Frequency Count	38	25		13		1,35	2.12	0.15	0.06
Saccade Duration Total	38	25		13		1,35	0.29	0.59	0.01
Saccade Duration Average	38	25		13		1,35	1.53	0.23	0.04
Saccade Duration Maximum	38	25		13		1,35	1.28	0.27	0.04
Saccade Duration Minimum	38	25		13		1,35	1.75	0.20	0.05

Table A2. *Cont.*

Type of Access	N	*n*	G1	*n*	G2	*df*	*F*	*p*	η^2
			M (SD)		*M (SD)*				
Saccade Amplitude Total	38	25		13		1,35	0.89	0.35	0.03
Saccade Amplitude Average	38	25		13		1,35	1.67	0.21	0.05
Saccade Amplitude Maximum	38	25		13		1,35	1.27	0.27	0.04
Saccade Amplitude Minimum	38	25		13		1,35	6.90	0.01 *	0.16
Saccade Velocity Total	38	25		13		1,35	0.09	0.77	0.003
Saccade Velocity Average	38	25		13		1,35	2.67	0.11	0.07
Saccade Velocity Maximum	38	25		13		1,35	0.04	0.85	0.001
Saccade Velocity Minimum	38	25		13		1,35	7.67	0.01 *	0.18
Saccade Latency Average	38	25		13		1,35	1.17	0.29	0.032
Blink Count	38	25		13		1,35	0.10	0.75	0.003
Blink Frequency Count	38	25		13		1,35	0.03	0.87	0.001
Blink Duration Total	38	25		13		1,35	1.55	0.22	0.04
Blink Duration Average	38	25		13		1,35	0.95	0.34	0.03
Blink Duration Maximum	38	25		13		1,35	0.95	0.34	0.03
Blink Duration Minimum	38	25		13		1,35	0.12	0.74	0.003
Scan Path Length	38	25		13		1,35	0.15	0.70	0.004

Note. G1 = novice participants; G2 = expert participants; *M* = mean; *SD* = standard deviation; *df* = degrees of freedom; η^2 = eta squared effect value; * $p < 0.05$.

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3.1.4.1. Estándares de calidad de la revista *Applied Sciences*

La revista está indexada en *Science Citation Index Expanded (WOS)*, Scopus y otras bases de datos.

Esta revista se encuentra en la base de datos *Journal Citation Report* en *Science Citation Index Expanded* (SCIE) dentro de la categoría *ENGINEERING, MULTIDISCIPLINARY - SCIE* en el segundo cuartil (Q2 JIF = 2.679) (Ver imagen 3.13). En el año 2020, en el momento en el que se publicó la aportación, la revista se situó en la posición 55 de 169 revistas, lo que la coloca en un Q2 con un *Journal Impact Factor* (JIF) de 2.679 y un *Journal Impact Factor Without Self Citations* de 2.219. En ESI en 2018 (último dato registrado en WOS) ocupa una posición de 211/893, es decir está en el primer cuartil (Q1).

Applied Sciences también está indexada en Scopus. La revista comienza a indexarse en 2011 en las categorías: *Computer Sciences and Materials Sciences Multidisciplinary Digital Publishing Institute* (MDPI). En 2015 registra un valor SJR (*Scimago Journal Rank*) de 1 =0.82, situándose en el primer cuartil de ambas categorías, actualmente tiene un H *index* de 23.

3.1.4.2. Índices de calidad del artículo 4

En la base de datos de la WOS este artículo, de momento, no cuenta con citaciones, pero tiene 65 referencias como puede verse en la imagen 3.14.

En los registros de la métrica de la revista (ver figura 3.12) desde la fecha de su publicación 2 de julio de 2021 el artículo ha sido visto en la página 341 veces y ha sido descargado más de 200 veces.

3.1.5. Artículo 5: *Improve teaching with modalities and collaborative groups in an LMS: an analysis of monitoring using visualisation techniques*

La revista *Journal of Computing in Higher Education* (ISSN 1042-1726; eISSN 1867-1233) publica investigaciones originales, revisiones bibliográficas, estudios de implementación y evaluación, y artículos teóricos, conceptuales y políticos que proporcionan perspectivas sobre el papel de la tecnología de la instrucción en la mejora del acceso, la asequibilidad y los resultados de la educación postsecundaria. Se da prioridad a los trabajos originales bien

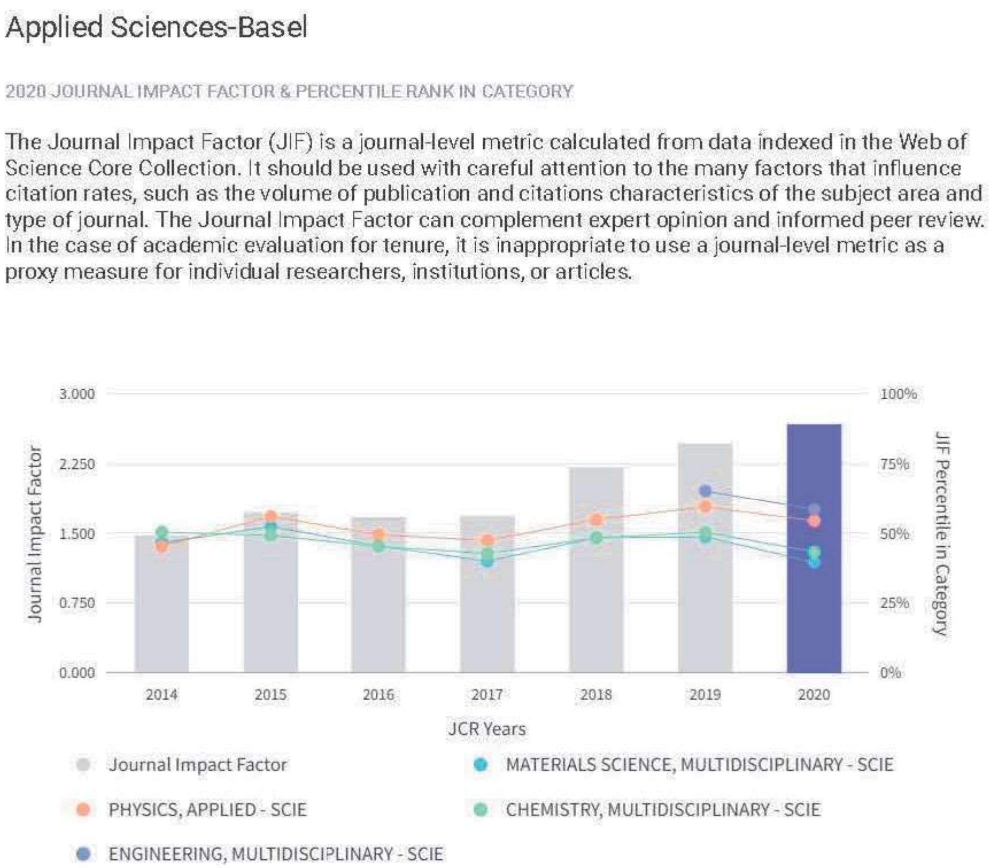

Figura 3.13: JIF de la revista *Applied Sciences* 2. Fuente: WOS (31/07/2021)

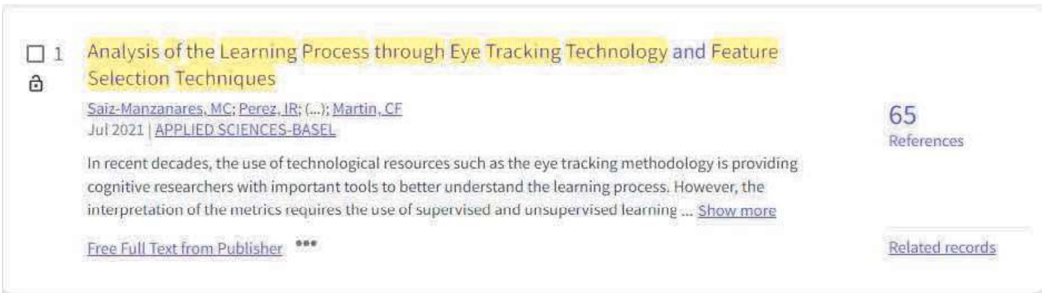

Figura 3.14: Citaciones del artículo 4. Fuente: WOS (31/07/2021)

Figura 3.15: Estadísticas del artículo 4. Fuente: *Applied Sciences* (07/09/2021)

documentados que demuestren una sólida base en la teoría del aprendizaje y/o un diseño de investigación educativa riguroso.

Esta revista cuenta con gran visibilidad ya que cuenta con altos índices de impacto y está indexada en WOS y Scopus entre otras bases de datos. La publicación no es rápida ya que la revisión por pares que realizan es muy exhaustiva y de media tardan 92 días en dar una primera respuesta del borrador y 432 días hasta la publicación del mismo.

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Improve teaching with modalities and collaborative groups in an LMS: an analysis of monitoring using visualisation techniques

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Abstract

Monitoring students in Learning Management Systems (LMS) throughout the teaching–learning process has been shown to be a very effective technique for detecting students at risk. Likewise, the teaching style in the LMS conditions, the type of student behaviours on the platform and the learning outcomes. The main objective of this study was to test the effectiveness of three teaching modalities (all using Online Project-based Learning -OPBL- and Flipped Classroom experiences and differing in the use of virtual laboratories and Intelligent Personal Assistant -IPA-) on Moodle behaviour and student performance taking into account the covariate "collaborative group". Both quantitative and qualitative research methods were used. With regard to the quantitative analysis, differences were found in student behaviour in Moodle and in learning outcomes, with respect to teaching modalities that included virtual laboratories. Similarly, the qualitative study also analysed the behaviour patterns found in each collaborative group in the three teaching modalities studied. The results indicate that the collaborative group homogenises the learning outcomes, but not the behaviour pattern of each member. Future research will address the analysis of collaborative behaviour in LMSs according to different variables (motivation and metacognitive strategies in students, number of members, interactions between students and teacher in the LMS, etc.).

Keywords Online project-based learning · Visualisation techniques · Machine learning techniques · Monitoring students · Self-regulated learning · Heat map

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Introduction

Nowadays, the teaching–learning process is increasingly carried out in online or blended learning environments, reducing the use of the purely face-to-face (F2F) modality. This situation has increased with the crisis due to COVID-19 (Sáiz-Manzanares et al., 2020b). Therefore, the way of learning and teaching is changing, since a high percentage of teaching is done through Learning Management Systems (LMS) (Sáiz-Manzanares et al., 2020b). One of the challenges in these environments is to analyse the development of cooperative learning among groups of students. This challenge is very important in teaching designed from a constructivist methodology such as Project-based learning (PBL). The PBL methodology focuses on the development of critical thinking, encourages creativity and the resolution of tasks specific to the degree in the future graduate. Moreover, collaborative work is one of the skills required by today's society and is recognised by organisations such as the Organisation for Economic Cooperation and Development (OECD) (OECD, 2019) and by the European Commission in the 2030 Agenda for education. The next section will deal with aspects related to active teaching methodology such as PBL applied in LMS environments in collaborative groups and the analysis of logs through Machine Learning and visualisation techniques during the monitoring of students throughout the teaching–learning process. The digital transformation involved in tackling this methodological change in teaching requires the acquisition and use of digital skills by the agents involved (teaching staff and students). This transformation was planned at the beginning of 2020 in a progressive development. However, the SAR-CoV-2 pandemic accelerated the acquisition of these strategies and their implementation in different professional, educational and social contexts (García-Peñalvo, 2021). Nevertheless, this supervening need does not imply that institutions and citizens were prepared to face the challenge. Although a huge effort has been made, especially in higher education institutions, it has become clear that there are gaps in digital strategies among both teaching staff and students. This fact points to the need to address the challenge of digital transformation with concrete training proposals. These include changes in teaching instruction (teaching style) and in the way students learn (learning style) (Cabero-Almenara and Llorente-Cejudo, 2020). Similarly, the feedback that the virtual learning environment must offer to the teacher and the student involves increasing the use of visualisation tools for the teaching–learning processes in the LMS (Álvarez-Arana et al., 2020). In recent years, the use of these Learning Analytics tools has been boosted in order to be able to easily analyse the large volume of data recorded in LMSs (Duin & Tham, 2020). These resources will make it possible to detect the learning patterns of each user and, depending on the learning results, propose the most appropriate curricular aids for the student to achieve the deepest and most effective learning possible (García-Peñalvo, 2020a). Therefore, it is important to include dashboards in virtual platforms that provide teachers with information to monitor their students' learning patterns in real time (Verbert et al., 2013). All of this opens up a new challenge, which is the integration of data in educational contexts in higher education and its processing through ecosystems or holistic environments for interpretation (Vázquez-Ingelmo et al., 2021). Such ecosystems entail institutional decision-making aimed at a necessary change already initiated by the health crisis situation (García-Peñalvo, 2020b; García-Peñalvo and Corell, 2020). All these aspects will be addressed in more depth below.

Background

Project-based learning, flipped classroom, and self-regulated learning in virtual environments

PBL is a teaching–learning method that is based on constructivism (Hmelo-Silver, 2004). It can be defined as student-centred instruction that occurs over an extended period of time during which students select, plan, research and create a product, a presentation or a development that answers a research question or problem (Holm, 2011). PBL focuses on the teaching–learning process, on the interaction of teacher and students, on the construction of deep learning from the design of tasks based on practical research and directed through reflection questions. All of this is based on continuous formative feedback in a collaborative learning framework (Doise et al., 1975). Current studies (Lajoie et al., 2015) indicate that an important factor for the successful development of PBLs is the use of interactive platforms such as LMSs, in this case the PBL is called Online Project-Based Learning (OPBL) (Yilmaz et al., 2020). Such environments are tools that facilitate co-regulation and the development of metacognitive strategies during task solving (Bannert et al., 2015). Therefore, LMSs enable the design and implementation of structured programmes for the development and activation of metacognitive strategies during learning. This fact facilitates the development of Self-regulated learning (SRL) (Bannert, et al., 2014), as they structure the necessary sub-goals in a stepwise manner, in order to achieve deep and successful learning from consecutive approaches to the goal. The reason is that the use of self-planning (Sáiz-Manzanares & Montero-García, 2015), monitoring and self-assessment strategies will increase self-awareness (Cloude et al, 2019). This is because the teaching–learning structure developed in LMSs based on OPBLs can activate students' prior knowledge through enquiry questions implicit in the development of OPBLs (Brand et al., 2019). Furthermore, LMSs allow for continuous monitoring and adaptation to the student's learning pace, which increases the use of metacognitive and motivational strategies during the learning process (Cloude et al., 2019). All of which will facilitate the generalisation of metacognitive skills to achieve learning objectives (Wiedbusch et al., 2021). Therefore, in this environment, collaborative student work in small groups can be implemented, which will facilitate the work dynamics within the PBL methodology (Shanmuganeethi et al., 2020). All this will make sustainable education possible by making profitable use of the resources that the teacher implements on the platform, as these resources will be used according to the students' learning styles (Sáiz-Manzanares et al., 2021a). In short, higher levels of performance, coupled with higher quality of learning by students, are achieved when students mobilize metacognitive skills and deep approaches in their learning process (Bártolo-Ribeiro et al., 2020). Especially in higher education, when it requires greater autonomy of students, the capacities for regulating cognition and learning are fundamental to assure academic achievement (Valadas et al., 2017). Recent research also shows that the use of hypermedia resources facilitates the development of deeper and higher quality learning (De Kock, 2016), as systematic planning through interactive platforms, where both audio and video elements are additionally combined, facilitates the development of metacognitive strategies during task solving. These platforms set the objective, the planning in the development of the resolution, the evaluation of the resolution steps and the evaluation of the final result from a respect for the student's learning pace (Sáiz-Manzanares et al., 2019a). Working from the OPBL methodology combined with the feedback resources that LMSs include further increases motivation and autonomy in student learning (Chen et al., 2020). However, this is a complex and difficult process to measure (Zhang et al., 2019). Recent research (Aikina & Bolsunovskaya, 2020) has found that the most important factors for increasing motivation are: automatic checking of exams, the possibility to publish news and additional learning material, setting individual assignments, organising collaborative learning online and having analytics to track student behaviour in LMSs similar to Moodle (Modular Object-Oriented Dynamic Learning Environment). Current research in this field is directed towards testing the type of relationships that are established within collaborative groups during the resolution of OPBLs. It has been found that cooperation based on a vertical structure in which one of the members of the collaborative group guides the work process is the most effective (Yilmaz et al., 2020). In this framework, the use of Flipped Classroom experiences has also been shown to be a very effective resource for enhancing SRL and increasing motivation (Noroozi et al., 2019) and the effective development of OPBL, as it improves the use of metacognitive strategies of self-planning and self-assessment (Yoon et al., 2021). On the other hand, the teacher's interpretation of the results of the learner interaction in the LMS requires the use of log analysis and interpretation systems. Possible resources include the use of visualisation and data mining techniques throughout the learning process. These tools will facilitate the detection of the learner at risk in each of the collaborative groups throughout the learning process, therefore these aspects will be discussed below. Likewise, recent study shows that the use of hypermedia resources facilitates the development of deeper and higher quality learning (De Kock, 2016), since systematic planning through interactive platforms, in which both audio and video elements are additionally combined, facilitates the development of metacognitive strategies during the resolution of tasks.

Learning management system relationship with self-regulated learning and metacognition: analysis using educational data mining techniques

Teaching work in LMSs within eLearning or Blended Learning environments is a practice that has been developing more and more frequently over the last decade. This has increased over the last year due to the COVID-19 pandemic. This practice refers to both formal and non-formal concepts of teaching and focuses on the importance of the human factor and interaction as an essential element in the learning process (García-Peñalvo and Seoane-Pardo, 2015). Nevertheless, the only use of LMS does not guarantee better learning outcomes (Agredo-Delgado et al., 2020). Such use is conditioned on the one hand by the teaching design and on the other hand by the type of feedback that the design includes on the evidence of learning. Recent studies (Park & Jo, 2017) have found significant differences in learning outcomes according to the teachers' teaching style and the learning style of students (Sáiz-Manzanares et al., 2021a). Another relevant aspect facilitated by LMSs is the early detection of at-risk students, Strang (2016) analyses the relationship between the use of LMSs and students' learning patterns on the platform (Sáiz-Manzanares et al., 2021b). In this line, regression analysis techniques, among others, make it possible to detect successful and risky behavioural patterns. These patterns explain up to 52% of the variance in learning outcomes. These studies are supported by the use of Data Mining (DM) techniques. The learning behaviours that have been considered referential for successful learning, among others, are (Cerezo et al., 2016):

- The time students spend on tasks.
- The time spent working on theoretical content.
- Results in self-assessment tests (quiz efforts).
- Time spent in forum discussions.
- The quality of the discussions in the forums (type of message and length of the message).
- Time spent analysing the feedback given by the teacher.
- The frequency of use of the LMS.
- Contribution to content creation.
- The files viewed.
- The delivery time of the activities.

Logs, learning analytics (LA) and educational data mining (EMD)

When the various participants in the learning process interact through an LMS, a series of logs or log files are generated that capture each of the interactions. These logs can be analysed. The use of DM will allow patterns to be isolated or new information to be extracted from the analysis of large data sets. When these techniques are used with data related to learning, we talk about Learning Analytics (LA) or Educational Data Mining (EDM) techniques. These concepts are closely related although they are not the same. LA focuses more on understanding the learning process (Agudo-Peregrina et al., 2014), specifically, these techniques investigate, among others, the answers to the following questions:

(1) Which data to analyse (what). The information recorded in the LMS is overwhelming, that is why it is necessary to detect data analysis patterns. (2) For whom this information is provided (who). It is important to discriminate the target group of the analysis (students, teachers, tutors/mentors, educational administrators, etc.). Students will be interested in more effective learning spaces. Teachers will be interested in how to make their teaching practices more effective and to offer the

support their students need, and institutions will be interested in detecting students at risk in order to increase success rates and avoid drop-out. For all these reasons, it is increasingly important to implement tools within LMSs that offer data analysis so that teachers, who are not experts in the application of EDM techniques, can understand and clarify the different situations that occur during the learning process. These techniques provide aim-oriented feedback that allows the user of the platform to reflect on their actions and guide them in their decision making. (3) Why information is provided. There are different objectives depending on the user role. LAs include monitoring analysis, i.e. tracking students in order to generate reports for the teacher and/or the institution. This information will help the teacher to evaluate the learning process in order to improve the learning environment and offer help to the student in order to increase the results. As well as the prediction of the student's knowledge and learning results in order to detect the student at risk and provide him/her, if needed, with the necessary help to achieve effective learning. In addition to implementing tutoring (learning guidance process) and mentoring (concrete plan of personalised help in planning and supervision issues and preparation of new challenges specifically for each student according to their needs), assessment and feedback (facilitates self-assessment processes that allow the student to succeed in learning). Intelligent feedback reports are produced and provided to both the teacher and the learner. 4) How information is provided. Methods for detecting hidden patterns of learning in LMSs can be done through statistical methods, data visualisation methods and DM techniques (Einhardt et al., 2016). The former in LMSs allow the extraction of reports based on teacher and learner interaction on the platform (online time, total number of visits, number of visits per page, distribution of the visits over time, frequency of replications, etc.). The most commonly used statistics are means (M) and standard deviations (SD). The second ones offer user-friendly reports on data distribution (e.g. heat maps, bar area charts, histograms, scatter plots, etc.). And the third ones can be supervised (classification and regression) and unsupervised (clustering) learning DMs and data association rules. All of them can provide information about models (Slater et al., 2017). In short, the EDM technique is multidisciplinary, converging techniques of algorithm construction, Artificial Neural NetWorks, instance-based learning, Bayesian learning, etc. These techniques can use different analysis procedures (Arnaiz-González et al., 2016) which can be grouped into clustering techniques, outlier detection techniques, association rule mining and sequential pattern mining and text mining (Romero and Ventura, 2007). Therefore, the use of one or the other will depend on the objectives of the task analysis. However, researchers in this field seek to predict the results in order to provide particular recommendations in each case. Regarding LMSs, one of the most widely used is Moodle, which allows the use of different resources for different learner profiles (individual and/or group) and teacher profiles. Moodle also makes it possible to carry out different learning activities and actions (discussion forums, questionnaires, workshops, wikis, access to repositories, etc.) and to use innovative teaching methodologies such as OPBL. The interactive behaviours that can be analysed on this type of LMS (Yücel & Usluel, 2016): student–student interaction, student–teacher interaction, student-content interaction, student-system interaction and teacher-system interaction. Yücel and Usluel (2016) point out that it is important to consider the type, quantity and quality of interactions. Each of these interactive behaviours is reflected in the logs. To facilitate their analysis, Moodle allows the extraction of these files in different formats: csv, xls, etc. The analysis of these files will provide a lot of information about the learning behaviours of the students, and the type of teaching of the professor. However, the information that can be obtained from Moodle log files is very extensive, so for a proper interpretation of the data it is necessary to use EDM (Agudo-Peregrina et al., 2014). Thus, EDM develops techniques and models that will facilitate the knowledge of students' learning behaviour patterns and the interactions between them (teacher-student, students-students). All of which supports continuous (formative) assessment processes. EDM can address different profiles (Romero and Ventura, 2007; Romero et al., 2013):

- Oriented towards students. This type of assessment is directed towards learning tasks and the aim is to improve the learning process in students.
- Oriented towards educators. The objective is to provide feedback to the teacher for instruction, evaluate the structure and contents of the course, analyse elements that have been effective in the learning processes, classify the type of students and see the needs for guidance and monitoring of learning. All this, to know the learning patterns of the students and the frequency of errors so that the teacher can implement the most effective activities.
- Oriented towards academics responsible and administration. The aim is to provide feedback to the institution to help improve learning platforms.

This functionality is very important in research on e-assessment models (Liyanage et al., 2016) that have to assess the learning strategies used by students, the environment in which learning takes place (Harrati et al., 2016), the design of teaching by the professor (Sáiz-Manzanares, 2018) and the use of active teaching methodologies (Sáiz-Manzanares & Montero-García, 2016), among others. In this area of research, it has been found that there are different patterns and learning outcomes depending on the type of e-assessment (Bogarín et al., 2018). In summary, the use of the methodologies described above will make it possible to detect patterns of student and teacher behaviour on the platform through the study of logs. Likewise, the EDMs will facilitate the study of behaviour and the development of cognitive-behavioural science (Jones, 2017).

Detecting students at risk of failure through LMSs

The detection of students at academic risk must be a priority objective for teachers and university institutions (Sáiz-Manzanares et al., 2017). In order to carry out an effective detection in LMSs, an analysis of the monitoring procedures that help to detect the learning patterns of each student is necessary (Cerezo, et al., 2017). These patterns explain up to 52% of the variance in learning outcomes. These studies are oriented from the use of EDM (Bogarín et al., 2018). In short, the frequency and systematicity of interaction on the platform by the learner together with the completion of self-assessment activities and average queries per day are aspects directly related to the achievement of effective learning (Sáiz-Manzanares et al., 2019b; Yücel & Usluel, 2016). The analysis of logs through EDM techniques will allow teachers to analyse the behaviour patterns of their students and predict the student at risk (Sáiz-Manzanares et al., 2019b). In addition, early intervention in these cases is likely to improve students' learning responses. Also, the use of LMSs will facilitate, especially in university settings, the structuring of collaborative teaching, which is expected to increase students' motivation towards the learning process (Järvelä et al., 2016). Recent studies confirm that monitoring students' learning patterns on the platform facilitates the discrimination of at-risk students with an explained variance of 67.2% (Bannert et al., 2014; Bogarín et al., 2018; Cerezo et al., 2016; Sáiz-Manzanares et al., 2021a). A summary of the points made in the introduction can be found in Fig. 1.

Personalisation of learning and e-Guidance

Recent studies in Higher Education indicate that teaching methodologies should be directed towards more personalised forms of interaction with the student (Sáiz-Manzanares et al., 2019b). Therefore, Higher Education is in a moment of change derived from the new demands of the knowledge society. This fact has been increased by the pandemic situation due to COVID-19, which has led to teaching being increasingly carried out through LMSs (Sáiz-Manzanares et al., 2020b). The digitisation of teaching as mentioned above implies the inclusion of digital tools and teacher training programmes that address aspects especially related to the design of learning tasks, assessment methods and feedback to student learning outcomes (García-Peñalvo et al., 2020). For this reason, it is necessary for the university lecturer to carry out a guidance task in the learning process of each student. Thus, student guidance at university must be structured from the design of teaching programmes that promote successful learning (Carbonero et al., 2013). Understanding the guidance function as an inherent value of the

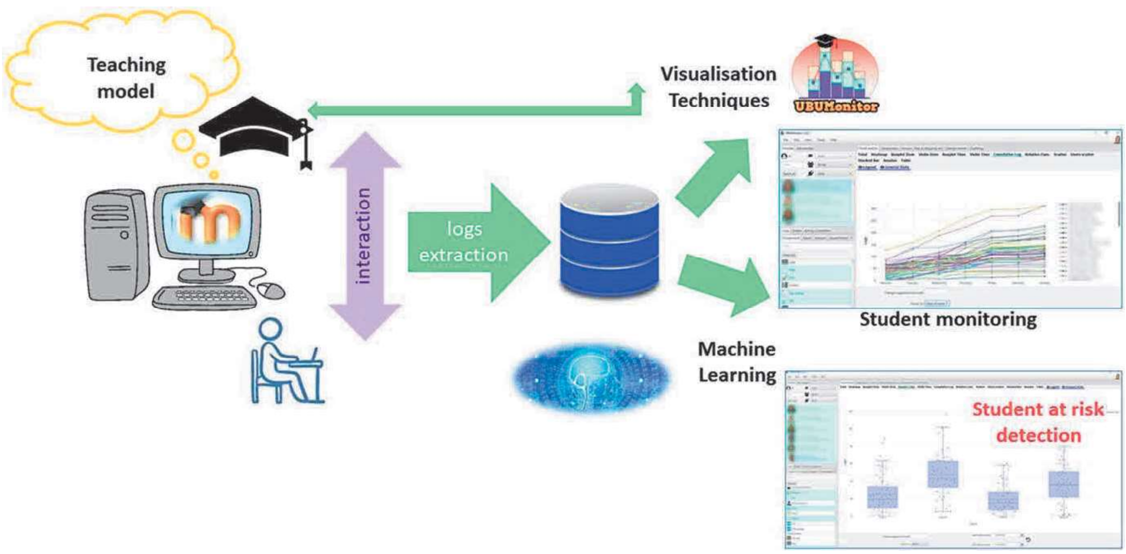

Fig. 1 Diagram of the teaching–learning process in Moodle applying process monitoring tools

teaching function (Sáiz-Manzanares & Román-Sánchez, 2011). In this field, new technologies have opened up a new environment for research in learning (Gros & García-Peñalvo, 2016; Lockee & Gros, 2020). As mentioned above, LMSs, such as Moodle, allow individualised monitoring of the teaching–learning process of each student. Recent studies indicate that personalised student tracking increases learning outcomes, frequency of interactions on the platform and motivation to learn. Likewise, such monitoring predicts students' learning outcomes by 61.3% and behaviour patterns in the LMS by 56.1% (Sáiz-Manzanares et al., 2017).

Based on the above-mentioned state of the art, the research questions of this work were:

Quantitative study

RQ1. Will there be significant differences between students' behaviours in the LMS as a function of the implemented teaching modality influenced by the covariate collaborative group?

RQ2. Will there be significant differences between students' learning outcomes in the LMS as a function of the implemented teaching modality influenced by the covariate collaborative group?

RQ3. Are there significant differences in students' satisfaction with the development of the teaching–learning process in the LMS depending on the implemented teaching modality influenced by the covariate collaborative group?

RQ4. Will the grouping clusters with respect to interactions in the LMS match the categorisation of collaborative groups with respect to achievement of learning outcomes?

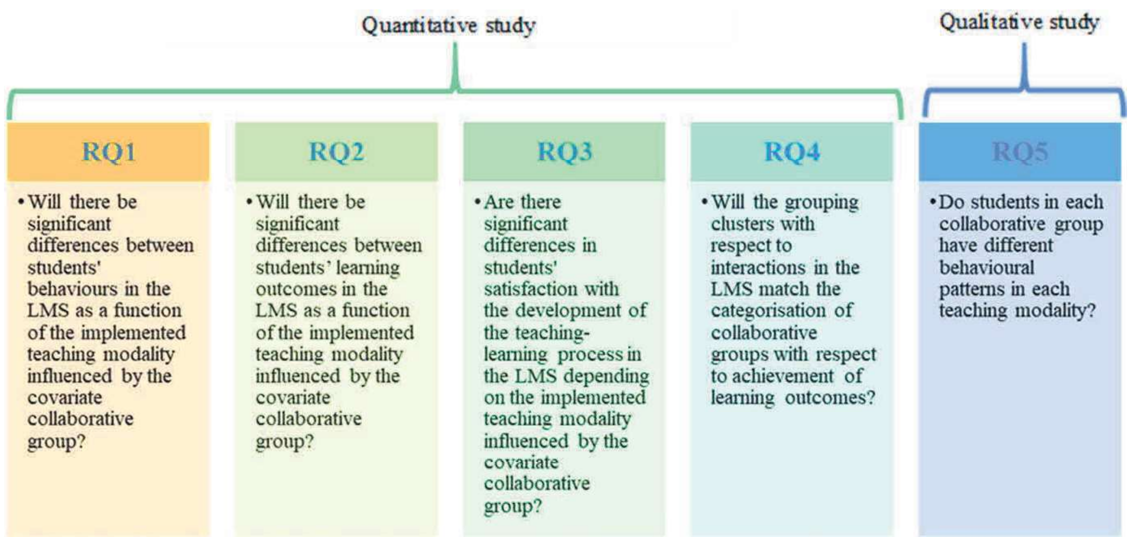

Fig. 2 Outline of relationship between type of study and research questions

Qualitative study

RQ5. Do students in each collaborative group have different behavioural patterns in each teaching modality?

A diagram of the procedure followed in each study can be found in Fig. 2.

Method

Participants

We worked with a sample of 143 students of third year in the Occupational Therapy degree applying convenience sampling, which was divided into three groups of the same subject. In each of them, a type of teaching modality was implemented (see the procedure section), three in total. In Mode A there were 55 students (49 women, mean age (Mage) = 22.6 and standard deviation (SDage) = 3.5 and 6 men, Mage = 23.7 and SDage = 1. 9), 42 students in Mode B (34 women Mage = 22.3; SDage = 1.6, and 8 men Mage = 22.5, SDage = 2), 46 students in Mode C (38 women, Mage = 22.4; SD = 2.25 and 8 men, Mage = 21.6; SD = 1.8). The higher percentage of women than men is common in Health Sciences, where the ratio according to the latest report of the Spanish University Rectors' Conference -CRUE- (Hernández-Armenteros and Pérez-García, 2019) is 73.8, an aspect that is confirmed in this study.

Within each modality the participants were in collaborative groups (they could choose with whom to form the group) made up of 3 to 6 participants, exceptionally and due to personal reasons of the students there could be groups made up of only one student, these groups were eliminated in this study. In Modality A, 13 groups were registered, in Modality B, 12 groups and in Modality C, 11 groups.

Instruments

a. UBUVirtual Platform. This platform is an LMS developed in a Moodle environment, version 3.9 was used.
b. Learning strategies scale (ACRA) by Román-Sánchez and Gallego Rico (2008). This scale is a highly contrasted instrument in research on learning strategies in Spanish-speaking populations (Carbonero et al., 2013). ACRA identifies 32 strategies at different stages of information processing. In this study, only the metacognitive scales were used, which include the subscales of self-knowledge, self-planning, and self-evaluation. It also has a Cronbach's reliability coefficient of $\alpha = 0.90$, an inter-rater construct validity of $r = 0.88$ and a content validity of $r = 0.88$.
c. Design of the subject. A teaching methodology based on the use of OPBL was applied. Especially, the course included five thematic units with the following structure: presentation of the unit, additional information, quiz-type question-

naires on the platform with automatic feedback and a satisfaction survey in each unit. However, dissimilar elements were differentiated depending on the teaching intervention modality: Modality A, included PBL, automatic product-oriented feedback on the answers given by the student (students were given information on the results obtained in the different activities) and Flipped Classroom experiences; Modality B, included PBL, automatic process-oriented feedback (students were given information on the results obtained in the different activities and information was included on why each answer was given and where they could find this information on the platform), Flipped Classroom experiences and virtual laboratories; Modality C, included PBL methodology, product-oriented feedback, Flipped Classroom experiences, virtual laboratories and the help of an Intelligent Personal Assistant (IPA) which informed the student about the events of the subject (Sáiz-Manzanares et al., 2020a).

d. Learning outcomes. The following assessment procedures were considered: PBL elaboration (had a weight of 25% in the total grade), PBL Presentation (had 20% of the final weight), Quiz (had 30% of the final weight). For this study, the grades in the practical exercises (25% of the weight) were not considered, as all students obtained the same grade (the methodology of "learning from error" was used, when the practical exercise did not obtain the maximum grade, it was returned for improvement until the student obtained the maximum grade, so this score was not discriminating), the total of the Learning outcomes was 100%.
e. UBUMonitor tool (Ji et al., 2018). UBUMonitor is a desktop application running on the client, implemented with Java, and with a graphical interface developed in JavaFX. The application connects to the selected Moodle server, through web services and REST API provided by the server. In the absence of web services to retrieve specific data, web scraping techniques are also used. All communication between the Moodle server and the UBUMonitor client is encrypted via HTTPS for security reasons. As a result of these queries, the data is obtained in JSON and CSV format, processed and transformed into Java objects in the client. For the visualisation of the collected data, the hybrid solution of applying Java and embedding web pages with different graphical JavaScript libraries within the desktop application is used. The data can be stored on the client to optimise access times for later queries and offline access to the data, using the serialisation mechanism available in Java. The serialised files with the subject data are stored encrypted with the Blowfish algorithm (Schneier, 1993). The application, which is open source and free of charge, includes six modules: visualisation (which offers the representation of the frequencies in different graphs: Heat Map, Boxplot, Violin, Scatter, etc.), comparison, forums, risk of dropping out (allows the detection of students who have not been connected for 7–15 days at certain times during the course), Calendar events and Clustering (allows for finding clusters by applying different algorithms such as *k*-means, Fuzzy *k*-means, etc.). Specifically, in this study we have used the visualisation module, which allows an analysis of the access frequencies in components, events, sections or course seen in Moodle with options to analyse the logs in different graphs (Heat Map has been chosen, as it offers the results with a numerical and colour visualisation of intensity throughout the duration of the course) in the development of the subject. All

Fig. 3 Heat map of the weekly monitoring of each of the students in a collaborative group in different components in Moodle

visualisation options allow export in graphical format and in.csv format, for the elaboration of reports and their subsequent analysis with other tools. The use of visualisation techniques such as Heat Map for the detection of students at risk is a tool that is proving to be very effective (Dobashi et al., 2019; Sáiz-Manzanares, et al., 2020b). An example of student monitoring within a collaborative group can be found in Fig. 3.

Procedure

We worked with three groups of third-year students in the Occupational Therapy Degree at the Faculty of Health Sciences of the University of Burgos. Prior to the study, a positive report was obtained from the bioethics committee of the University of Burgos, followed by written informed consent from all study participants. Before the intervention, the normality of the sample distribution and the homogeneity of the groups in the results of the Metacognitive Strategies Scale of Román-Sánchez and Gallego Rico (2008) were checked. This scale was applied to each group of students within each teaching intervention modality. Table 1 shows an outline of the

Table 1 Modalities of intervention with their corresponding teaching methodologies applied

Modality	Teaching methodology
Modality A	Online Project-based learning (OPBL) Quizzes with product-oriented feedback Flipped Classroom
Modality B	Online Project-based learning (OPBL) Quizzes with process-oriented feedback Flipped Classroom Virtual laboratories
Modality C	Online Project-based learning (OPBL) Quizzes with process-oriented feedback Flipped classroom Virtual laboratories Intelligent Personal Assistant (IPA)

teaching methodologies in each intervention modality applied. The distribution of the teaching methodology was carried out using convenience sampling. The teaching was given by the same professor in order to eliminate the extraneous variable "type of teacher".

The students' learning behaviour was studied in Moodle throughout the course in the three teaching modalities. In all the modalities, students worked with the OPBL methodology and were distributed in collaborative groups that were formed according to students' preferences, the ratio of the groups ranging between 3 and 6 members. Also, the learning outcomes in the different assessment procedures were analysed. The performance of each collaborative group was categorised with respect to the total grade in three categories: (1) medium performance: scores between 7.9 and 8.5; (2) high performance: scores between 8.5 and 9.5 and (3) very high performance: scores between 9.6 and 10), the category of low performance was not applied, as the lowest score obtained by the students in Learning outcomes total was equal to 7.9. The duration of the teaching in the three modalities was 9 weeks, and follow-up measurements were established with the UBUMonitor tool in which the Heat Maps were found: a first initial follow-up measurement after two weeks, an intermediate measurement after six weeks and a final measurement after eight weeks. A summary of the procedure is presented in Fig. 4.

Designs

Both quantitative and qualitative research designs were applied to test the research questions. For the quantitative research a 3×5×4 factorial quasi-experimental design was used (Campbell and Stanley, 2005) and for the qualitative research (Anguera et al., 2018) a longitudinal comparative design was used (Flick, 2014).

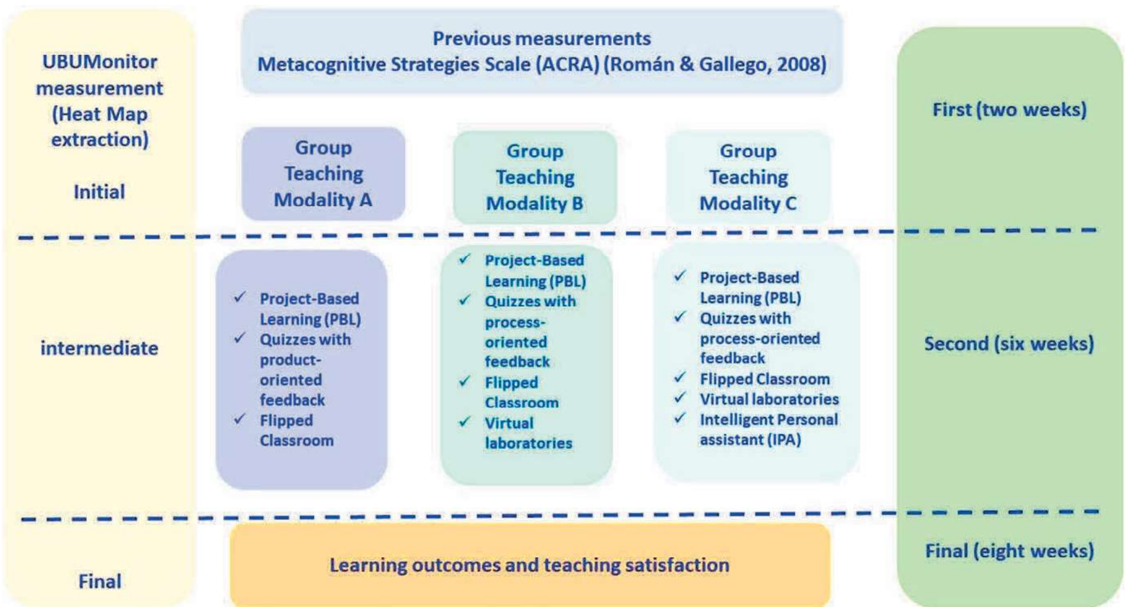

Fig. 4 Research development procedure

Data analysis

An analysis of the normality of the sample was carried out by applying skewness and kurtosis statistics, then to check the homogeneity in the three groups before the intervention in the results of the Metacognitive Strategies Scale (Román-Sánchez & Gallego Rico, 2008) a one-factor ANOVA was used with fixed effects "modality type" and eta-squared effect value (η^2) [a small effect is considered to be the interval between 0.10 and 0.29, a medium effect the interval between 0.30 and 0.49 and high the interval between 0.50 and 1 (Cohen, 1988)]. Subsequently, to test Research Questions (RQ) RQ1, RQ2 and RQ3, a one-factor ANCOVA with fixed effects "modality type" and covariate "collaborative group" was applied. To contrast RQ4, Principal Component Analysis (PCA), Machine Learning techniques of unsupervised learning (clustering), ANOVA, cross-tabulation, and Pearson's contingency coefficient (this expresses the intensity of the relationship between two or more qualitative variables. It is based on the comparison of the actually calculated frequencies of two characteristics with the frequencies that would have been expected irrespective of these characteristics) are used. The statistical package SPSS v.24 (IBM, 2016) was used to perform these analyses. In addition, visualisation techniques, in particular Heat Map, were used to contrast RQ5 using the UBUMonitor software (Ji et al., 2018). Also, qualitative analysis techniques of Heat Map categorisation and analysis of the frequencies found in the categorisation and Sankey plots were used (this is a specific flow chart in which the width of the bands is proportional to the amount of flow and serves to visualise transfers of X elements between processes. This type of diagram puts a visual emphasis on the important transfers within a system and helps to locate the dominant contributions to a total flow). The software ATLAS.ti 9 (ATLAS.ti, 2020) was used for its generation.

Results

Previous statistical analyses

Previously, in order to check the normality of the distribution, the skewness and kurtosis statistics were found with respect to the results on the Metacognitive Strategies Scale of Román-Sánchez and Gallego Rico (2008). No extreme values were found for skewness [Self-knowledge $A = -1.18$; Self-planning and regulation $A = -0.36$; Self-assessment $A = -1.06$, extreme values are considered those greater than $|2.00|$] or kurtosis [Self-knowledge $K = 3.49$; Self-planning and regulation $K = 0.53$; Self-assessment $K = 2.71$, extreme values are considered those between $|8.00|$ and $|20.00|$] (Bandalos & Finney, 2001). (Bandalos & Finney, 2001) so it can be deduced that the sample follows a normal distribution. Therefore, parametric statistics were applied.

Next, in order to check the homogeneity between the groups before the intervention in the three modalities, a one-factor ANOVA with fixed effects " modality type" was carried out with respect to the results found in the Román-Sánchez and Gallego Rico (2008) metacognitive strategies scale. As can be seen in Table 2, no significant differences were found between the students assigned to the three modalities. Thus,

Table 2 ANOVA of a fixed effects factor "modality type" in the ACRA Metacognitive Strategies scale (Román-Sánchez & Gallego Rico, 2008)

Metacognitive scale	N	n	G1 M (SD)	n	G2 M (SD)	n	G3 M (SD)	df	F	p	η^2
Self-knowledge	143	55	20.6 (2)	42	20.2 (2.5)	46	19.6 (3.2)	(142,2)	1.7	0.2	0.02
Self-planning	143	55	11.8 (2.5)	42	11.9 (2.5)	46	12.2 (2.4)	(142,2)	0.4	0.6	0.006
Self-assessment	143	55	19.24 (2.7)	42	18.7 (2.8)	46	19.3 (3.3)	(142,2)	0.5	0.6	0.006

G1 = Modality A; G2 = Modality B; G3 = Modality C; M = Mean; SD = Standard Deviation; df = degrees of freedom, η^2 = eta-squared effect value

parametric statistics were applied to test the research questions within the quantitative research study.

Quantitative study

To test RQ1, a one-factor fixed-effect ANCOVA was performed on the type of modality and the covariate collaborative group. Significant differences were found in all types of accesses as well as in the average number of visits per day between the three modalities. However, there was no significant effect of the covariate "collaborative group". The highest averages for accesses to complementary information, accesses to the guidelines for OPBL, as well as the average number of visits per day were found in Modality C. Nevertheless, in Modality A, the highest mean was found for accesses to feedback. The effect values were medium for accesses to Supplementary Information and mean number of visits per day and low for the remaining variables (see Table 3).

To test RQ2, a one-factor ANCOVA with fixed effects was performed on the type of modality and the covariate collaborative group. Significant differences in learning outcomes were found in the assessment procedures PBL elaboration, PBL presentation and in total learning outcomes and were not found in quizzes. Also, the effect values were low in all learning outcomes except PBL elaboration and Learning outcomes total, which were medium. In addition, the effect of the covariate "collaborative group" was found in all types of learning outcomes (see Table 4).

Likewise, the drop-out rate in modality A and B was 0% and in modality C 0.02%, and the success rates (percentage of successful students out of the students presented in the first and second sittings) were 98.2% in Modality A; 100% in Modality B; and 100% in Modality C, respectively. This is relevant considering that the average success rate in the other subjects of the academic year was, respectively, 91.9%, 71.2% and 83.9%. This indicates a difference of 6.3, 28.8 and 16.1 percentage points.

To test RQ3, a one-factor fixed-effects ANCOVA was performed on the type of modality and the covariate collaborative group. No significant differences were found in student satisfaction with the teaching modality (see Table 5).

To test RQ4 beforehand, a Principal Component Analysis (PCA) was performed and a KMO = 0.22, χ^2 = 124.87, p = 0.00 was obtained. Two components were isolated: component 1, which included the following dependent variables: accesses to

Table 3 ANCOVA of a fixed effects factor "modality type", covariate "collaborative group" with respect to platform accesses

Type of access	N	*n*	G1 *M (SD)*	*n*	G2 *M (SD)*	*n*	G3 *M (SD)*	*df*	*F*	*p*	η^2
Independent variable											
Supplementary information	143	55	38.02 (23.45)	42	19.36 (13.23)	46	77.91 (45.12)	(142, 2)	41.00	0.00*	0.37
OPBL Guidelines	143	55	5.09 (6.30)	42	11.86 (8.24)	46	31.22 (29.35)	(142, 2)	26.72	0.00*	0.28
Co-evaluation	143	55	26.93 (16.17)	42	7.93 (6.76)	46	22.15 (17.70)	(142, 2)	20.71	0.00*	0.23
Feedback	143	55	116.78 (45.84)	42	71.71 (24.40)	46	78.91 (25.04)	(142, 2)	24.53	0.00*	0.26
Average number of accesses per day	143	55	3.54 (1.21)	42	1.90 (0.51)	46	4.49 (1.68)	(142, 2)	40.69	0.00*	0.40
Co-variable											
Supplementary information	143	55		42		46		(142, 2)	0.17	0.68	0.001
OPBL Guidelines	143	55		42		46		(142, 2)	0.18	0.90	0.000
Co-evaluation	143	55		42		46		(142, 2)	0.005	0.95	0.001
Feedback	143	55		42		46		(142, 2)	0.13	0.72	0.001
Average number of accesses per day	143	55		42		46		(142, 2)	0.15	0.70	0.001

*$p < 0.05$. Note: G1 = Modality A; G2 = Modality B; G3 = Modality C; *M* = Mean; *SD* = Standard Deviation; *df* = degrees of freedom, η^2 = eta squared effect value

Table 4 ANCOVA of one fixed effects factor "modality type", covariate "collaborative group" on learning outcomes

Type of access	N	*n*	G1 *M (SD)*	*n*	G2 *M (SD)*		G3 *M (SD)*	*df*	*F*	*p*	η^2
Independent variable											
PBL elaboration			2.29 (0.12)	42	2.35 (0.10)	46	2.19 (0.19)	(142, 2)	13.93	0.00*	0.17
PBL Presentation			1.70 (1.17)	42	1.66 (0.24)	46	1.90 (0.13)	(142, 2)	36.74	0.00*	0.35
Quiz			2.72 (0.24)	42	2.63 (0.13)	46	2.65 (0.22)	(142, 2)	2.21	0.11	0.03
Learning outcomes total			9.09 (0.49)	42	8.90 (0.40)	46	8.90 (0.47)	(142, 2)	2.50	0.09	0.04
Co-variable											
PBL elaboration				42		46		(142, 2)	61.85	0.00*	0.31
PBL Presentation				42		46		(142, 2)	33.34	0.00*	0.19
Quiz				42		46		(142, 2)	31.49	0.00*	0.19
Learning outcomes total				42		46		(142, 2)	114.85	0.00*	0.45

G1 = Modality A; G2 = Modality B; G3 = Modality C; *M* = Mean; *SD* = Standard Deviation; *df* = degrees of freedom, η^2 = eta-squared effect value

$^*p < 0.05$

Table 5 ANCOVA of one fixed effects factor "modality type”, covariate "collaborative group" on student satisfaction with teaching

Type of access	N	*n*	G1 *M (SD)*	*n*	G2 *M (SD)*		G3 *M (SD)*	*df*	*F*	*p*	η^2
Independent variable											
Satisfaction with teaching			4.40 (0.39)	42	4.38 (0.33)	46	4.48 (0.32)	(141, 2)	1.30	0.28	0.002
Co-variable											
Collaborative group									1.30	0.28	0.02

G1 = Modality A; G2 = Modality B; G3 = Modality C; *M* = Mean; *SD* = Standard Deviation; *df* = degrees of freedom, η^2 = eta-squared effect value

$^{*}p < 0.05$

Table 6 Final cluster centres

Access	Cluster		
	Acceptable n = 69	Good n = 50	Excellent n = 24
Supplementary information	28	35	116
OPBL Guidelines	13	5	44
Co-evaluation	10	25	35
Feedback	64	130	91
Average visits per day	2.26	3.67	5.87

Table 7 ANOVA between clusters

Type of access	N	*Cluster mean square*	*Root mean square error*	*df*	*F*	*p*
Supplementary information	143	71963.80	461.73	(2,140)	155.86	0.0001*
OPBL Guidelines	143	12552.26	260.38	(2,140)	48.21	0.0001*
Co-evaluation	143	6722.31	182.97	(2,140)	36.74	0.0001*
Feedback	143	62796.68	709.24	(2,140)	88.54	0.0001*
Average visits per day	143	119.63	1.14	(2,140)	104.62	0.0001*

*$p < 0.05$

complementary information, explained variance = 0.83; accesses to co-evaluation, explained variance = 0.84 and average number of views per day, explained variance = 0.69 and component 2, which included accesses to feedback, explained variance = 0.98 and accesses to guidance to perform the PBL, explained variance = 0.65. Both components explained 68.50% of the variance.

Next, a cluster analysis was carried out using the *k-means* algorithm with respect to the students' access to the platform in the three teaching modalities. Three grouping clusters were found. Cluster 2 was considered as: Excellent cluster 2, as it had the best values for most of the attributes, except for accesses to teacher feedback which was ranked second; Good, cluster 1, and Acceptable cluster 3. None of the clusters were considered to have bad values, as the data reflected interaction in the LMS for all types of accesses (see Table 6).

Also, an ANOVA was performed between the values found in the clusters between all types of accesses (see Table 7).

Next, we tested whether the variables selected as indicators of LMS use were equally sustainable in the cluster configuration. The three clusters explained 66% variance [Wilks' Lambda = 0.12; F (5, 10) = 52.68; $p < 0.000$, $\eta^2 = 0.66$]. This implies that students had different behavioural patterns of learning in the three clusters across the five types of access. However, not all access types had the same degree of discrimination. In the analysis of intergroup differentiation the variables that contributed most to differentiation were: accesses to supplementary information with a high effect value [$F(2, 140) = 155.86$, $p < 0.000$, $\eta^2 = 0.70$]; mean number of visits per day [$F(2, 140) = 104.62$, $p = 0.000$, $\eta^2 = 0.60$], the

Table 8 Crosstabulation: number of cluster cases by cluster categorisation with respect to the collaborative group

		Categorisation of Learning outcomes in collaborative groups						*n*
		1 *n* = 28	%	2 *n* = 94	%	3 *n* = 21	%	
Cluster case number	1	10	20	27	54	13	26	50
	2	5	41.67	18	75	1	4.16	24
	3	13	18.84	49	70.01	7	10.50	69

Categorisation of Learning outcomes in the collaborative groups 1 = medium performance: scores between 7.9 and 8.5, 2 = high performance: scores between 8.5 and 9.5 and, and 3 = very high performance: scores between 9.6 and 10.

Fig. 5 Heat map on the weekly monitoring of a collaborative group in Moodle

accesses to the feedback given by the teacher with a mean effect value [$F(2, 140) = 88.54$, $p = 0.000$, $\eta^2 = 0.56$], the accesses to the OPBL orientations with a mean effect value [$F(2, 140) = 48.21$, $p = 000$, $\eta^2 = 0.41$] and the accesses to the co-assessment with a mean effect value [$F(2, 140) = 36.74$, $p = 0.000$, $\eta^2 = 0.34$].

Finally, the relationship between the distribution of the clusters and the categorisation of the learning outcomes in the collaborative groups was cross tabulated and the contingency coefficient was found to be $C = 0.24$, not significant at 95% $p = 0.06$ (see Table 8). This shows that the relationship between the assignment clusters and the categorisation of the collaborative groups was small. In other words, the grouping of students in the clusters does not exactly match the categorisation of students' performance according to the learning outcomes obtained in each of the collaborative groups. This fact may be an indicator that students' behaviour in Moodle is not homogeneous within each of the collaborative groups.

Qualitative study

In order to test RQ5, a qualitative analysis was carried out in which the following steps were applied:

Step 1 Heat maps were found in each of the collaborative groups within each teaching modality using the UBUMonitor tool (Ji et al., 2018, 2020). An example of the Heat Maps found can be found in Fig. 5.

Step 2 Heat Map images from each collaborative group were included in the software for the Atlas.ti 9 qualitative data analysis software.

Step 3 Heat Map were categorised in each collaborative group by teaching modality, establishing the following criteria according to the frequency of observed non-interaction: “Continuous work throughout the subject” (implies continuous student work throughout the subject, i.e. frequency of access in all weeks); “Non-interaction at the start of the subject” (implies non-interaction in the first two weeks of the subject); “Non-interaction in the middle of the subject” (implies non-interaction between the third and sixth week) and “Non-interaction at the end of the subject” (refers to non-interaction between the seventh and eighth week).

Step 4 Sankey plots were found for each modality. Also, a frequency analysis was carried out for each of the categorisation criteria established in each teaching modality.

A schematic of the steps followed in the qualitative study is presented in Fig. 6.

Figure 7 shows the analysis of frequencies per categorisation criterion in a Sankey chart within Modality A. The groups with the highest frequencies (≥ 50%) for the criterion "Continuous work throughout the subject" were groups 5, 9, 10, 11 and 13. The group with the lowest interactions (≥ than 50% non-interaction) with “Non-interaction at the end of the subject” was group 3. The groups with the lowest interactions (≥ 50% non-interaction) at the start of the subject were 1, 2, 3, 4, and 6. The group with the lowest interactions (≥ 50% non-interaction) in the middle of the subject was group 7.

Figure 8 shows the distribution of the collaborative groups within Modality B: the groups that worked continuously (≥ 50%) were collaborative groups 3, 6, 7, 8, and 9. The groups with a lower interaction (≥ 50%) towards the middle of the course were groups 1, 2, 4, 5, 7, and 12. Likewise, no non-interactions (≥ 50%) were detected at the start or end of the subject.

Figure 9 shows the distribution of the collaborative groups within Modality C: the collaborative groups that had continuous interaction (≥ 50%) throughout the course in this case was group 7. The collaborative groups in which non-interaction (≥ 50% non-interaction) was detected towards the middle of the course were groups 4 and

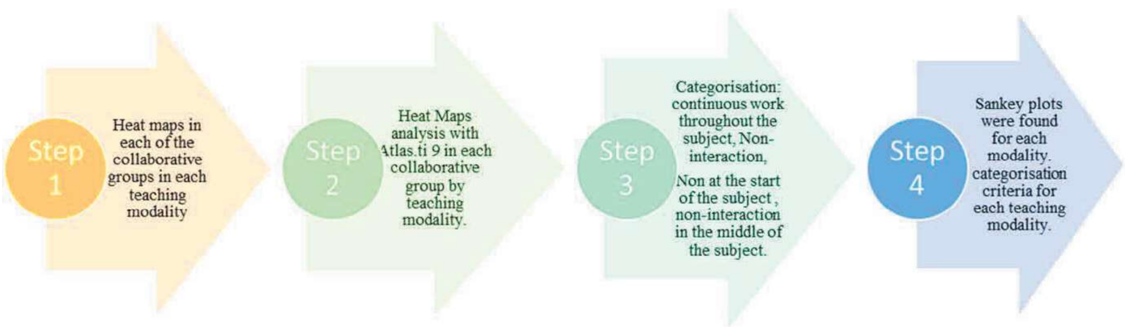

Fig. 6 Steps followed in the qualitative study

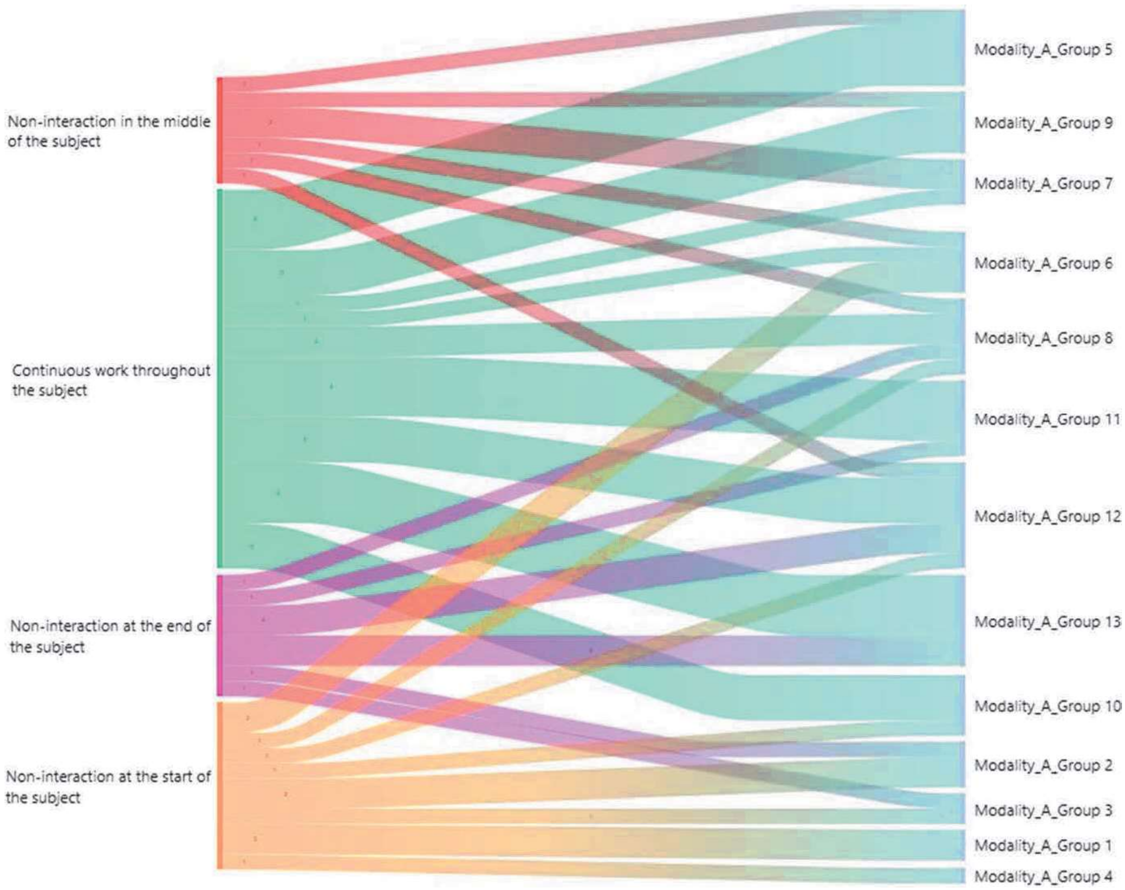

Fig. 7 Sankey chart in teaching Modality A

11, and at the end of the course groups 4, 5, and 6. Likewise, no non-interactions ($\geq 50\%$) were detected at the start of the subject.

Discussion

Regarding RQ1 (Will there be significant differences between students' behaviours in the LMS as a function of the implemented teaching modality influenced by the covariate collaborative group?), it was found that the teaching design does influence student behaviour in Moodle, although no effect of the covariate "collaborative group" was found. Specifically, the average number of accesses was higher in Modality C in the additional information, the guidelines for taking the OPBL and the average number of visits per day. However, a higher rate of accesses to the feedback was found in Modality A. The explanation may be that in Modality C a process-oriented feedback was used in which the score obtained was explained to the students with a detailed explanation of the reason for each correct or incorrect answer in addition to the grade while, in Modality A, a product-oriented feedback was used, in this case only information about the grade was given to the students. Concerning RQ2 (Will there be significant differences between students' learning outcomes in the LMS as a function of the implemented teaching modality influenced by the covariate collaborative group?), the type of teaching modality was found to

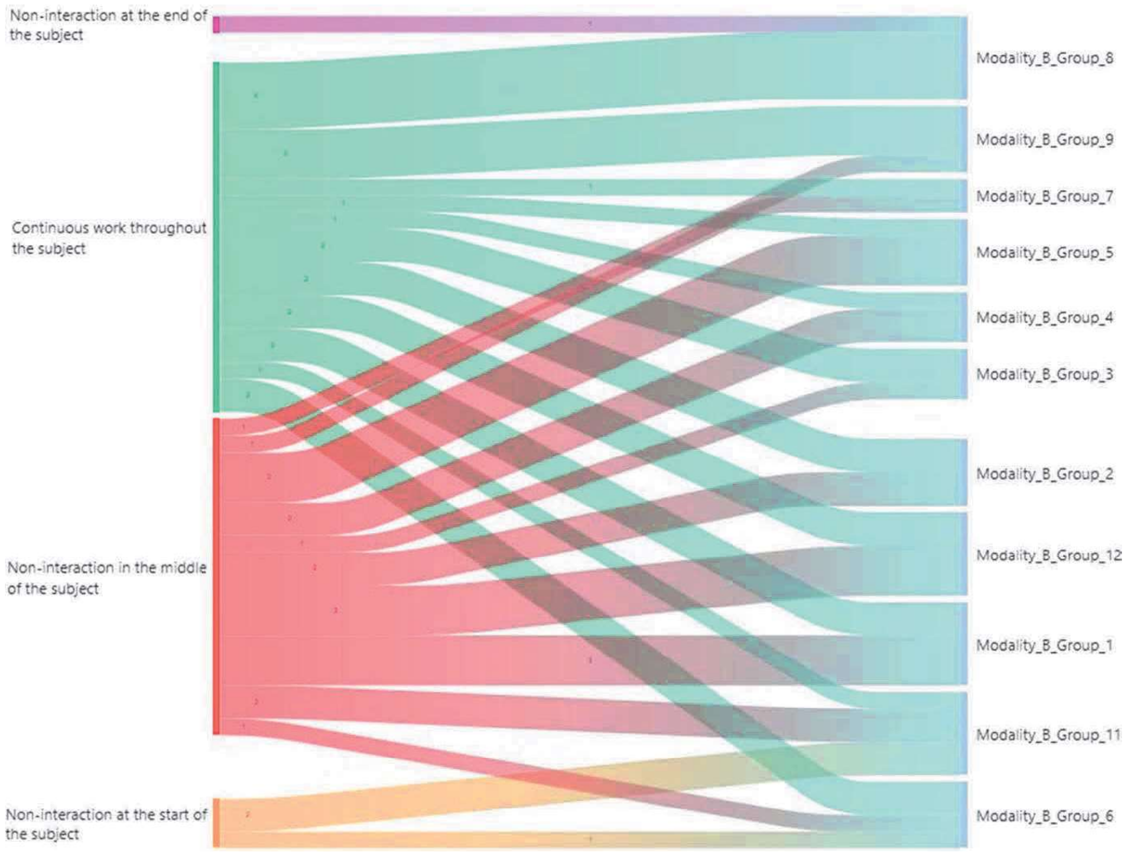

Fig. 8 Sankey chart in teaching Modality B

influence learning outcomes in all assessment tests except for quiz-type tests. In this case, the covariate collaborative group type did have an effect on all learning outcomes. The explanation may be that quiz grades involve individual rather than collaborative work. Therefore, the group does not compensate for the results, and in the other assessment tests collaborative work improves the learning outcomes of each student. Thus, it can be concluded that the teaching design seems to directly affect the collaborative work of the groups (Sáiz-Manzanares, 2018). Related to this explanation is the hypothesis that one of the members of the collaborative group performs leader functions and makes the differences within the members of each group compensate (Järvelä et al., 2016). In this line, the results found in the qualitative analysis corroborate this hypothesis as differences in behaviour between each of the members in Moodle have been found and visualised in the heat maps. These results verify the findings of Park and Jo (2017) and Yilmaz et al. (2020). In summary, each student has a learning style (Harrati et al., 2016) and this is an element to be considered by the teacher for the design of the subject (Sáiz-Manzanares et al., 2021a). Based on this, the learning environment in the LMS has to offer students several resources (visual, auditory and blended) and different assessment procedures (Bogarín et al., 2018) including process-oriented feedback and not only product-oriented feedback (Aikina & Bolsunovskaya, 2020; Chen et al., 2020; Liyanage et al., 2016) so that each learner can choose to access information in the way that best relates to the method they learn (De Kock, 2016; Sáiz-Manzanares et al., 2019c).

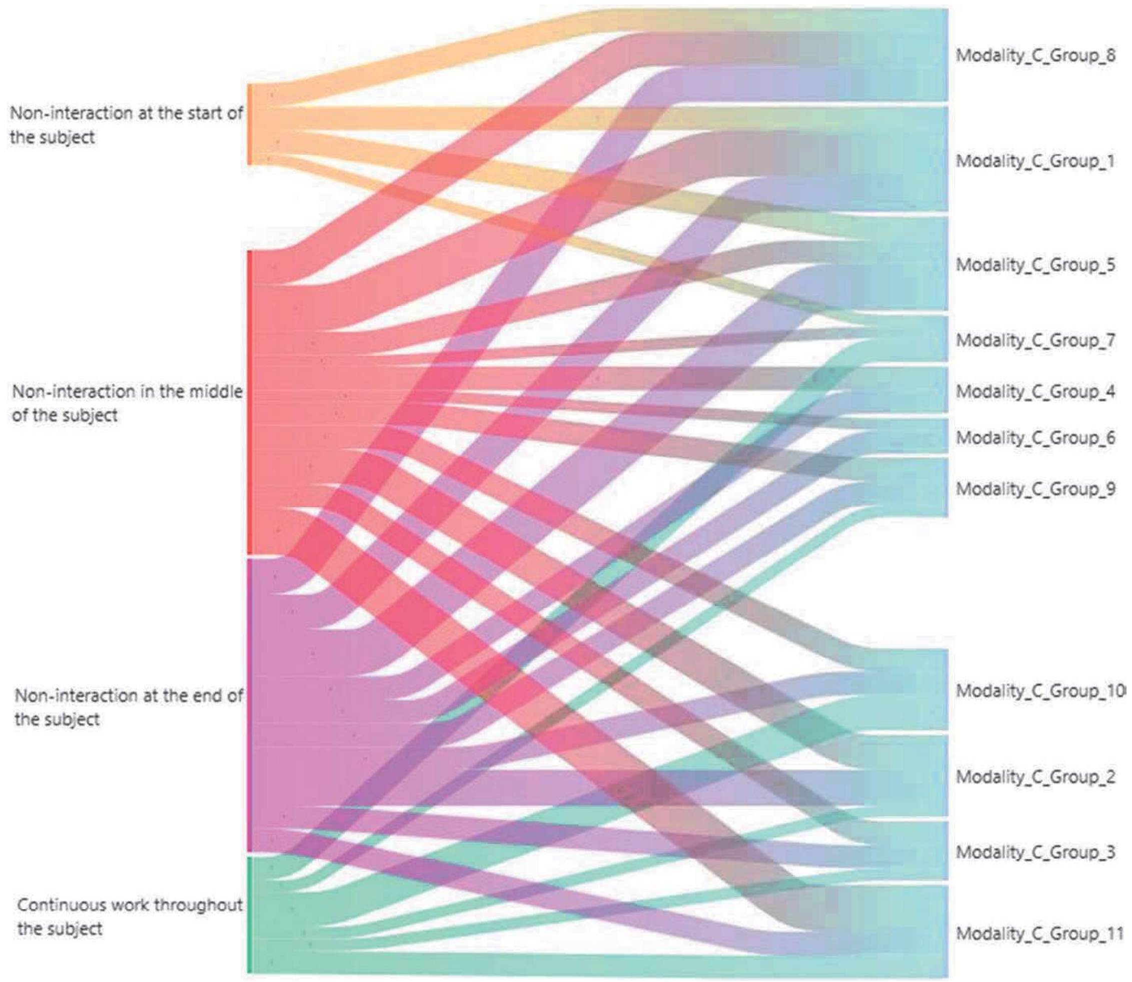

Fig. 9 Sankey chart in teaching Modality C

Regarding RQ 3 (Are there significant differences in students' satisfaction with the development of the teaching–learning process in the LMS depending on the implemented teaching modality influenced by the covariate collaborative group?) no significant differences were found between the three modalities implemented. One possible explanation is that all the teaching modalities studied included a constructivist methodology based on OPBL (Chen et al., 2020; Sáiz-Manzanares & Montero-García, 2016) with Flipped Classroom experiences (Yilmaz et al., 2020) and feedback to the assignments implemented in Moodle. Such teaching modality facilitates SRL and motivation towards learning (Järvelä et al., 2016; Noroozi et al., 2019).

With regard to RQ4 (Will the grouping clusters with respect to interactions in the LMS match the categorisation of collaborative groups with respect to achievement of learning outcomes?) this study aimed to find out was whether the grouping carried out in terms of the categorisation of the collaborative groups (very good, good, acceptable) with respect to the learning outcomes in Moodle corresponded with the grouping that could be obtained through clustering techniques, and it was found that there was no correspondence. This fact reinforces the idea that the behaviour of the members of a group is not homogeneous and that within each group there is a leader (Yilmaz et al., 2020). It has been shown that this type of dynamic within the collaborative group is more effective for the overall group performance than a structure on the same level as suggested by Doise et al. (1975).

Finally, concerning RQ5 (Do students in each collaborative group have different behavioural patterns in each teaching modality?) it has been found that the behavioural profiles within each collaborative group, that are represented in Heat Map, do not have a homogeneous pattern of interaction between the members of each collaborative group and that there are always one or two members in each group who set the pace of work (Dobashi et al., 2019; Sáiz-Manzanares et al., 2020b). Therefore, it can be concluded that monitoring the learning process in each student is essential throughout the entire development for the detection of students at risk, especially in the initial and intermediate phases of the learning process (Bannert et al., 2014; Bogarín et al., 2018; Cerezo et al., 2016; Sáiz-Manzanares et al., 2021b). Ideally, an initial measurement should be taken two weeks into the course, an intermediate measurement (in the middle of the course) and a final measurement (one or two weeks before the end of the course). Also, different interaction patterns have been found within each of the collaborative groups in each teaching modality among the members of each workgroup. In order to know this data, the LMS needs to have this analysis functionality or enable connection to tools such as UBUMonitor (Ji et al., 2018) that allow the visualisation of this data to be easily consulted using different techniques (Heat Map, Boxplot, Scatter, Stacked Bar, etc.). UBUMonitor has proved to be a very useful tool for this purpose, as it allows for easy monitoring of each of the students in Moodle at different periods of the teaching process (analysis by days, weeks or months) in the different components. In addition, this resource facilitates more complete EDM studies such as cluster analysis (Agudo-Peregrina et al., 2014).

In sum, the qualitative micro-analysis of the behaviour of small groups in LMSs applying OBPL is diverse, although a more or less systematic interaction can be detected throughout the course of the subject. It is relevant that despite the differences, no non-interaction was detected in any of the modalities during the course. There are, however, intra- and inter-modal oscillations. Therefore, future studies will be aimed at finding out which are the best interaction patterns and which differentiating characteristics (students' motivation, cognitive and metacognitive strategies they use, etc.). The ultimate goal will be to propose instructional programmes that support intra- and intergroup functioning.

Conclusions

This work has focused on studying different teaching modalities based on the use of active methodologies applied in Moodle and their relationship with student behaviour on the platform, learning outcomes and satisfaction with the teaching process. It has been found that although the teaching modalities include active methodologies, they do not have the same results in terms of behavioural profiles or student learning outcomes (Cabero-Almenara and Llorente-Cejudo, 2020). This is a significant element for reflection, since these differences may be due to various factors related to the students' own characteristics, such as digital competences (García-Peñalvo, 2021), cognitive, metacognitive, affective strategies, etc. (Bártolo-Ribeiro et al., 2020; Cloude et al., 2019; Wiedbusch et al., 2021; Yilmaz et al., 2020; Yoon et al., 2021), learning style and their response to Self-regulated learning (Valadas et al., 2017) or teacher characteristics, also related to digital competences and teaching style. These aspects will be addressed in future studies. Another relevant aspect to be studied in future work is the relationship dynamics within the collaborative groups; it has been detected that the interaction dynamics of the participants is not homogeneous. Similarly, another relevant element to be studied in detail is the use of visualisation resources for monitoring students (Álvarez-Arana et al., 2020; García-Peñalvo, 2020a; Verbert et al., 2013), such as UBUMonitor. These tools facilitate the functional monitoring of students in the LMS and allow the teacher to detect students who do not have a continuous learning pattern. However, if the teacher wishes to apply more complex techniques such as Machine Learning, it also facilitates their implementation (Vázquez-Ingelmo et al., 2021). In this study, it was found that the level of student performance and satisfaction was high, although not homogeneous, in the three teaching modalities applied. This conclusion shows that active methodologies are a good vehicle to encourage participation in virtual platforms and to achieve deeper learning (Chen et al., 2020; De Kock, 2016; García-Peñalvo, 2020a; Noroozi et al., 2019). Nevertheless, there are several factors that are influencing the results to be inconsistent. Therefore, directing research towards the detection of these factors is a relevant task for the twenty-first century society. In short, just the use of innovative methodologies applied in virtual platforms does not ensure learning success for all students (Agredo-Delgado et al., 2020). Among the possible factors that may explain this fact, the digital competence of the teacher and the student play an important role. Therefore, fostering the training of teachers and students (García-Peñalvo et al., 2020) is an important challenge for Higher Education institutions.

To sum up, the promotion of this type of teaching together with monitoring throughout the learning process is essential to achieve a more sustainable and inclusive education as supported by the OECD (2019) and the European Commission in the 2030 Agenda. This is the challenge for teachers and educational leaders especially in the framework of Higher Education which is geared towards reducing dropout and ensuring that students acquire competences that will enable them to work effectively and successfully on graduation.

Limitations and future work

The limitations of this work are related to the selection of the sample, since for ethical reasons it was not possible to randomise the groups to the different teaching modalities. Also, the sample is specific to third-year Health Science students. In addition, the composition of the groups was 3–6 participants and was not tested with more members, so the generalisation of the results should be made with caution. However, future studies will extend the type of participants to other areas of knowledge and in different academic years. Within we will check whether there are differences in behavioural profiles according to the number of members in each collaborative group (3, 4, 5, etc.).

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Declarations

Conflicts of interest The authors declare that they have no conflict of interest.

Ethical Approval Prior to the start of the study, a positive report was obtained from the Bioethics Committee of the University of Burgos, No. IR 30/2019.

Informed consent Participation was voluntary with no financial compensation. In addition, a written informed commitment was collected from all participants.

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María Consuelo Sáiz-Manzanares She has degree in Psychology from University of Salamanca, Spain, in 1986, and in Education Sciences from UNED, Spain in 2003. Also, She is PhD in Psychology from University of Valladolid, Spain, in 1994 and PhD in Industrial Technologies from University of Burgos, Spain, in 2019. Currently, she is professor in the Department of Health Sciences at the University of Burgos (Spain). Also, She is director of the Research Group DATAHES (Data Analysis Techniques Applied in Health Environments Sciences). Her lines of research are the study of metacognitive strategies in students and the use of data mining techniques applied to the improvement of learning and therapeutic intervention. More information https://investigacion.ubu.es/investigadores/35511/detalle.

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Juan José Rodríguez-Diez received the BS, MS and Ph.D. degrees in Computer Science from the University of Valladolid, Spain, in 1994, 1998 and 2004, respectively. He worked with the Department of Computer Science, University of Valladolid from 1995 to 2000. Currently, he is working with the Department of Computer Science at Universidad de Burgos, Spain, where he is a Professor. His interests include data science, machine learning and pattern recognition. He has worked on methods for classifier and regression ensembles, time series, feature selection, instance selection, multi-output, and big data; with industrial, health, bioinformatics, and educational applications. More information https://investigacion.ubu.es/investigadores/35480/detalle.

Sandra Rodríguez-Arribas has a degree in Computer Engineering from the University of Salamanca, a master's degree in Teacher Training in ESO, BACH, FP, and a master's degree in Intelligent Massive Data Analysis (Big Data) from the University Isabel I. She is currently an associate professor in the Computer Engineering Department at the University of Burgos and a member of the DATAHES (Data Analysis Techniques Applied in Health Environments Sciences) Research Group. More information https://investigacion.ubu.es/investigadores/36987/detalle.

José Francisco Díez-Pastor received his BS and ME in Computer Science and his PhD from the University of Burgos. He has been working since 2000 at the University of Burgos, teaching programming and conducting research in the field of learning analytics. He is currently the coordinator of the degree in health engineering. He is also a member of the BEST-AI research group https://investigacion.ubu.es/grupos/1819/detalle. His lines of research focus on data mining and artificial intelligence techniques applied to health sciences and learning in virtual systems.

Yi Peng Ji received his BS in Computer Science from the University of Burgos. In 2019 he participated in a research contract for the development of Machine Learning as a Service algorithm. A software developer responsible for UBUMonitor, he worked as a Data Analysis Technician at the Virtual Teaching Centre (UBUCEV) of the Universidad de Burgos.

3.1.5.1. Estándares de calidad de la revista *Journal of Computing in Higher Education*

Es una revista indexada en *Social Sciences Citation Index* (SSCI) en la categoría de *EDUCATION & EDUCATIONAL RESEARCH – SSCI* (ver imagen 3.16). En el año 2020, último año del que se tienen datos de análisis en WOS la revista se situó en la posición 106 de 264 revistas, lo que implica un Q2 con un *Journal Impact Factor* (JIF) de 2.627 y un *Journal Impact Factor Without Self Citations* de 2.542. También, tiene un Journal Citation Indicator (JCI) igual a 1.91.

Esta revista también está indexada en Scopus y tiene un H *Index* igual a 36. Tiene un SJR igual a 1.282 y en el último año con datos de indexación es un Q1.

Además la revista también está indexada en la clasificación CIRC (Clasificación Integrada de Revistas Científicas), y clasificada como grupo A que según los editores del producto, un comité de expertos en evaluación científica, el grupo de revistas clasificadas como A está "integrado por las revistas científicas de mayor nivel. Pertenecerían al mismo las revistas internacionales de mayor prestigio que han superado procesos de evaluación muy exigentes para el ingreso en diferentes bases de datos".

3.1.5.2. Estándares de calidad del artículo 5

Esta aportación tiene 0 citas y 65 Referencias (ver imagen 3.17) en la *Web of Science*, siendo la media de citas de la revista de 1 como se puede observar en la imagen 3.18.

En las métricas de la revista desde la fecha de publicación, 13 de julio de 2021, el artículo se ha visto 425 veces, las métricas son accesibles a través de: `https://link.springer.com/article/10.1007\%2Fs12528-021-09289-9/metrics`

3.1.6. Artículo 6: *Eye-tracking Technology and Data-mining Techniquesused for a Behavioral Analysis of Adults engaged inLearning Processes*

Journal of Visualized Experiments (Jove) (ISSN: 1940-087X). Es una revista norteamericana que aborda estudios experimentales con inclusión de un vídeo en protocolo sobre los ámbitos de la biología, las ciencias médicas y de

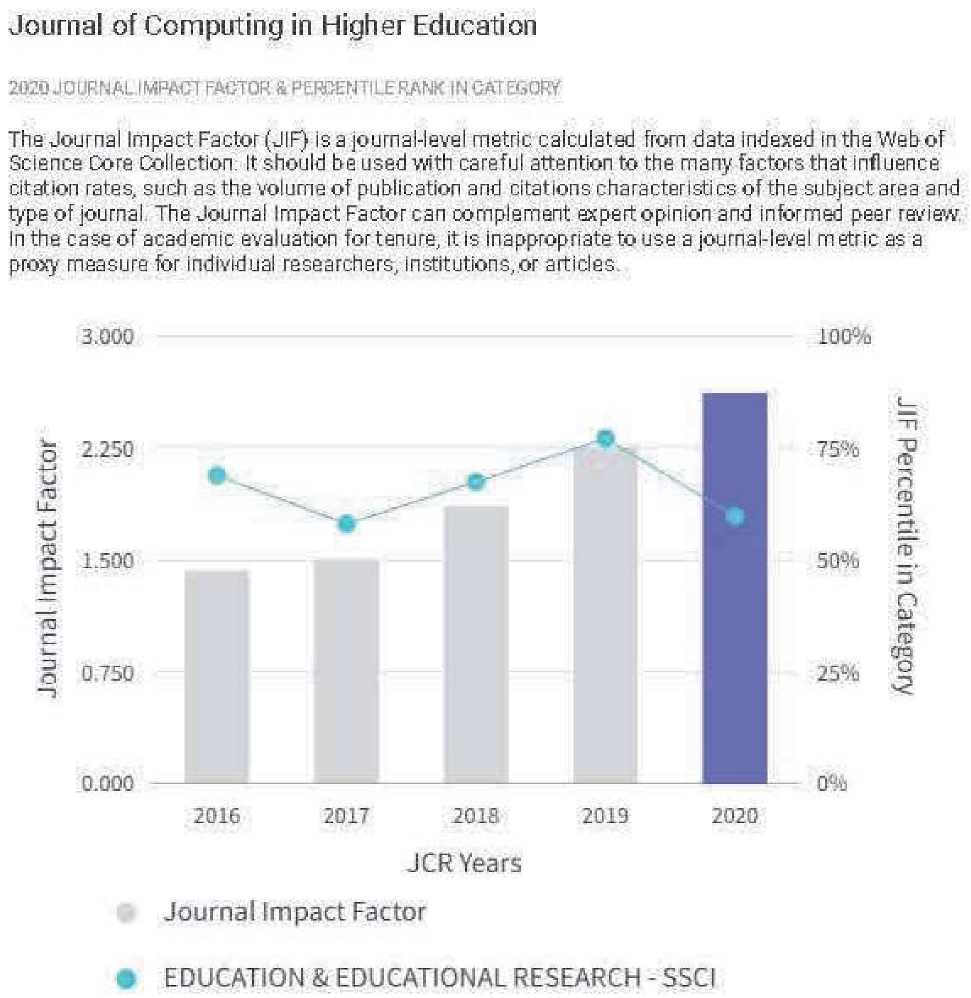

Figura 3.16: JIF de la revista *Journal of Computing in Higher Education*. Fuente: WOS (31/07/2021)

Figura 3.17: Citaciones del artículo 5. Fuente: WOS (31/07/2021)

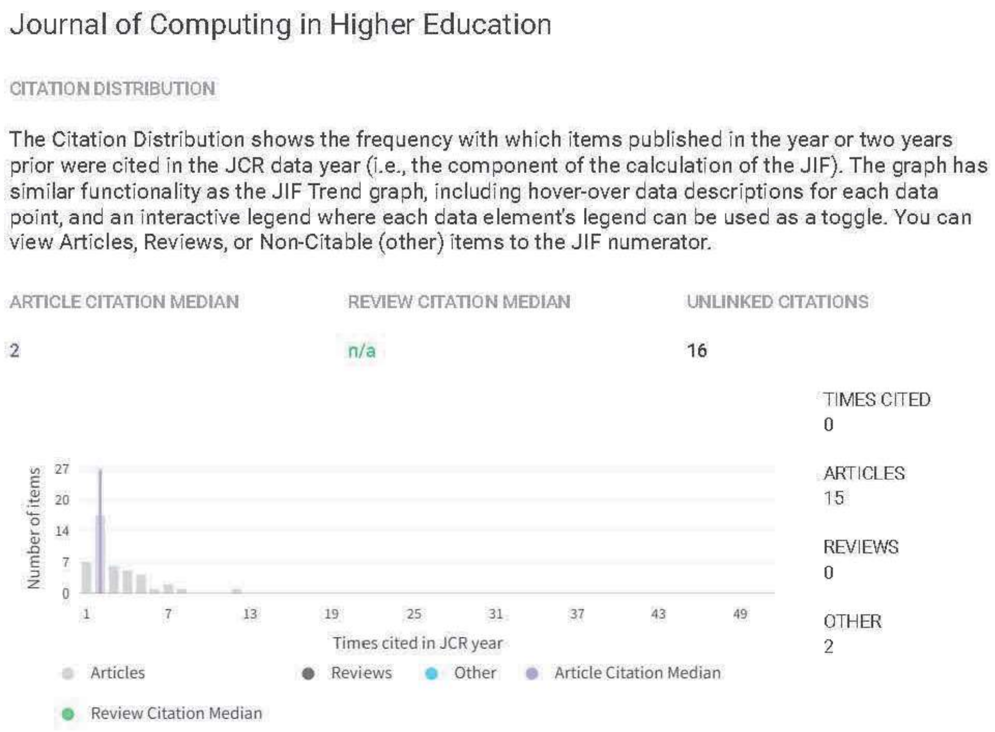

Figura 3.18: Citaciones de la revista *Journal of Computing in Higher Education.* Fuente: WOS (31/07/2021)

la salud, la ingeniería industrial y la química. Se sitúa en el campo académico de la ingeniería química y las neurociencias. La revista esta indexada en distintas bases de datos como WOS y Scopus.

Este artículo forma parte de la investigación del proyecto europeo "*Self-Regulated Learning in SmartArt*" (2019-1-ES01-KA204-065615).

3.1.6.1. Estándares de calidad de la revista Jove

La revista *Journal of Visualized Experiments* está indexada en la base de datos de la *Web Of Science* dentro de *Science Citation Index Expanded* (SCIE) en la categoría de *MULTIDISCIPLINARY SCIENCES* como puede comprobarse en la imagen 3.19. En último registro, año 2020, tiene un *Journal Impact Factor* (JIF) de 1.355 y un *Journal Impact Factor Without Self Citations* de 1.309. En el año de publicación de la aportación, 2020, se registró un JIF de 1.355, lo que la situaba en la posición 49 de 73 revistas (Q3).

La revista también está indexada en Scopus donde tiene un H *index* de 29 = +3.5 En el ámbito de BIOLOGÍA; CIENCIAS MÉDICAS Y DE LA SALUD; INGENIERÍA INDUSTRIAL; QUÍMICA.

3.1.6.2. Estándares de calidad del artículo 6

Esta aportación tiene 0 referencias en la *Web of Science*, siendo la media de citas de la revista de 0, en parte debido a que no es una revista de acceso abierto. Ver imágenes 3.20 y 3.21.

3.2. Otras publicaciones relacionadas

3.2.1. Capítulos de libro

Seguidamente se referencian los capítulos de libro en los que he colaborado.

1. Blended learning: an experience with infographics and virtual laboratories using Self-Regulated learning 13th International Technology, Education and Development Conference. Proceedings of INTED2019 Conference 11th-13th (IATED), pp. 2966-2971

2. Computer application for the registration and automation of the correction of a functional skills detection scale in Early Care 13th International Technology, Education and Development Conference. Proceedings of INTED2019 Conference 11th-13th (IATED), pp. 5322-5328

3. Design of a smartart classroom in art history: a learnign experience with sef-regulated serious games. INTED2019 Proceedings 11th-13th March 2019: 13th International Technology, Education and Development Conference (Iated Academy S.L), pp. 1998-2006

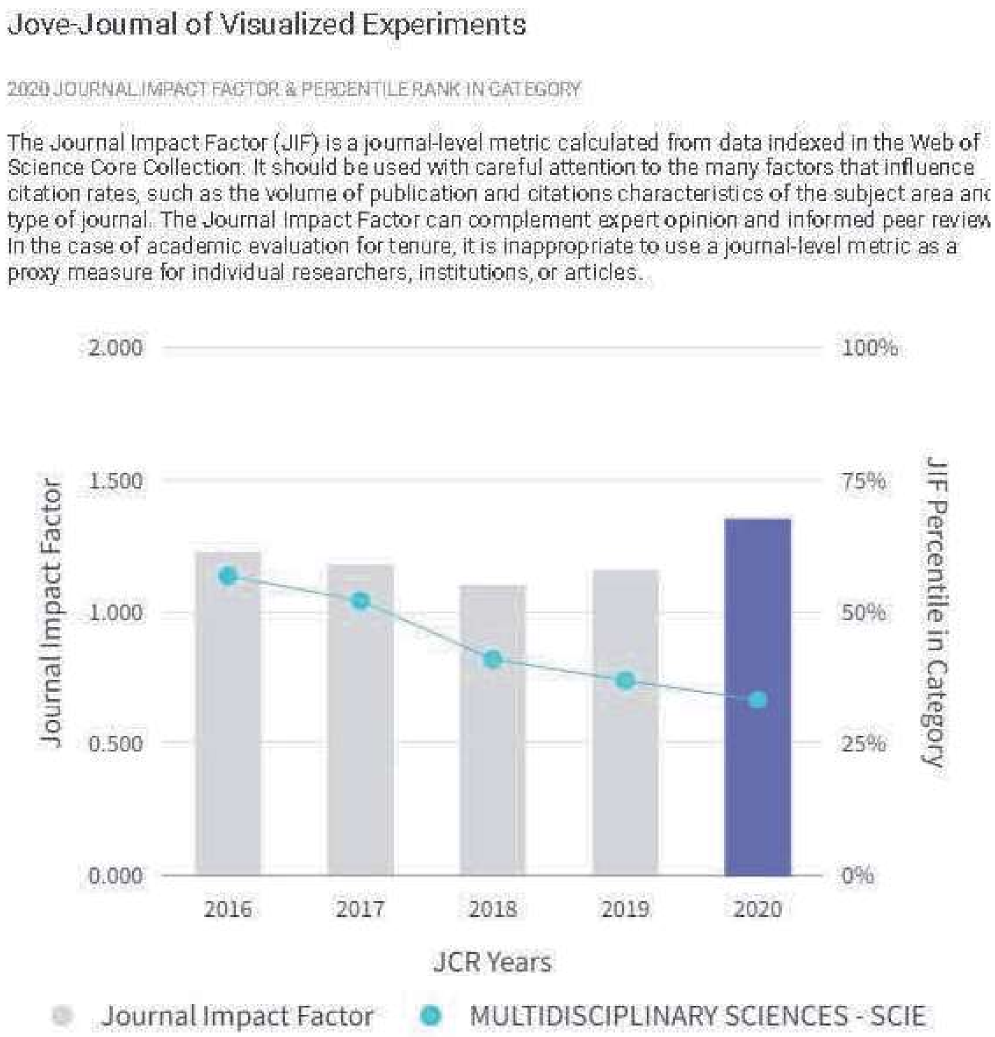

Figura 3.19: JIF de la revista *Journal of Visualized Experiments*. Fuente: WOS (31/07/2021)

Figura 3.20: Citaciones del artículo 6. Fuente: WOS (31/07/2021)

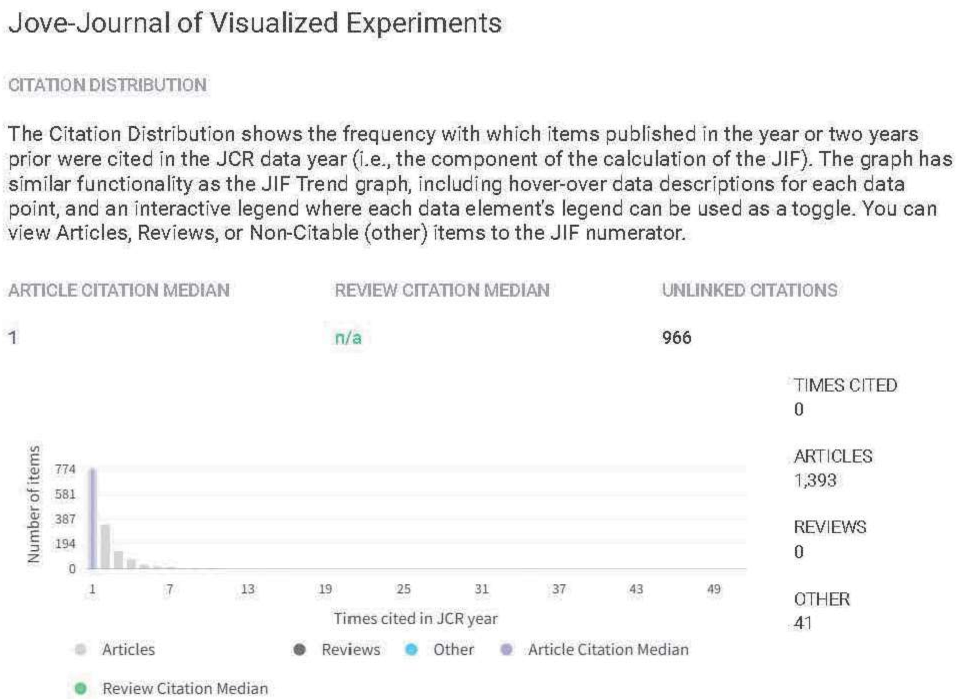

Figura 3.21: Citaciones de la revista *Journal of Visualized Experiments*. Fuente: WOS (31/07/2021)

4. Design of a virtual platform for learning the historand of art. Variables psicológicas y educativas para la intervención en el ámbito escolar: nuevas realidades de análisis (Dykinson), pp. 217-226

5. Detection of students at risk at university: prevention and guidance through a module. Variables psicológicas y educativas para la intervención en el ámbito escolar: nuevas realidades de análisis (Dykinson), pp. 207-216

3.3. Proyectos de investigación

A continuación se presentan como méritos adicionales a esta tesis doctoral los proyectos de investigación en los que he colaborado. A modo de resumen aparecen en tablas los datos principales de cada proyecto. El proyecto *Self-Regulated Learning in SmartArt* dispone, además, de página web (`https://srlsmartart.eu/`) en la que se puede consultar toda la información relativa al proyecto.

Título:	***Self-Regulated Learning in SmartArt***		
Entidad financiadora:	SEPIE		
Investigador responsable:	María Consuelo Sáiz Manzanares		
Participación en calidad de:	Colaboradora		
REFERENCIA	TIPO PROYECTO	DURACIÓN	IMPORTE
2019-1-ES01-KA204-065615	Erasmus +	1.sep.19-31.ago.22	221886 €

Tabla 3.1: Proyecto SmartArt

Título:	**e-Orientación en Moodle**		
Entidad financiadora:	Junta de Castilla y León		
Investigador responsable:	María Consuelo Sáiz Manzanares		
Participación en calidad de:	Colaboradora		
REFERENCIA	TIPO PROYECTO	DURACIÓN	IMPORTE
R02WG3 EDU/667/2019	Proyecto Autonómico	10.oct.19-30.sep.21	12000 €

Tabla 3.2: Proyecto e-orientación

Título:	**Igualdad de género en materias científico-tecnológicas**		
Entidad financiadora:	Junta de Castilla y León		
Investigador responsable:	María Consuelo Sáiz Manzanares		
Participación en calidad de:	Colaboradora		
REFERENCIA	TIPO PROYECTO	DURACIÓN	IMPORTE
EDUCYL2018_04	Proyecto Autonómico	01.sep.17-31.may.20	5000 €

Tabla 3.3: Proyecto Igualdad de género en materias científico-tecnológicas

Título:	**Asistentes de voz e inteligencia artificial en Moodle**		
Entidad financiadora:	Ministerio de Ciencia e Innovación		
Investigador responsable:	María Consuelo Sáiz Manzanares		
Participación en calidad de:	Colaboradora		
REFERENCIA	TIPO PROYECTO	DURACIÓN	IMPORTE
PID2020-117111RB-I00	Proyecto nacional I+D+i	2021-2023	50941 €.

Tabla 3.4: Proyecto Asistentes de voz e inteligencia artificial en Moodle

3.4. Otros méritos y acciones de difusión

3.4.1. Proyecto de Innovación Docente

El proyecto "Creación de Laboratorios Virtuales en UBUVirtual apoyo a la docencia en Ciencias de la Salud, Educación e Ingeniería Informática" en el que colaboro ha sido elegido en la "Convocatoria de Ayudas a Grupos de Innovación Docente reconocidos para la elaboración de materiales docentes para los años 2021 y 2022" de la Universidad de Burgos (UBU). El proyecto ha ha sido beneficiario de 1000 € siendo el primero en orden de puntuación, con 28 puntos.

Es un proyecto en el que participamos los miembros del Grupo de Innovación Docente de la UBU BLENDED LEARNING EN CIENCIAS DE LA SALUD (B[1]LCS) que se encargará de la creación de laboratorios virtuales para distintas asignaturas y ramas de conocimiento. Dicho proyecto se llevará a cabo durante el curso académico 2021/2022.

3.4.2. Proyecto Empresarial

Digital Artificial Intelligence Solutions in Health and Education (DAISHE): Soluciones digitales en el ámbito educativo y herramientas para la atención a personas dependientes es un proyecto, que ha sido seleccionado por la Junta de Castilla y León, con el segundo premio en la categoría de “Proyecto Empresarial” dentro de la convocatoria para la Transferencia de Conocimiento Universidad - Empresa (TCUE) en la edición 2020 del concurso “Iniciativa Campus Emprendedor”.

El proyecto, liderado por María Consuelo Sáiz Manzanares, cuenta con una financiación de 9000 € para la creación de una *spin-off* de la Universidad de Burgos. En él colaboramos varios miembros del profesorado de la UBU pertenecientes a diversas ramas de conocimiento.

3.4.3. Comunicaciones en congresos

Por último en este apartado de méritos adicionales, se exponen las distintas comunicaciones realizadas en congresos.

Tipo:	Comunicación oral
Autores:	María Consuelo Sáiz Manzanares, Sandra Rodríguez Arribas y Raúl Marticorena
Título:	Computer aplication for the registration and automation of the corecction of a functional skills detection in early care
Congreso:	13th International technology, educations and development conference
Lugar:	Valencia
Fecha:	11, 12 y 13 de marzo de 2019

Tabla 3.5: Datos comunicación oral 1 en el congreso INTED 2019

Tipo:	Comunicación oral
Autores:	María Consuelo Sáiz Manzanares, Raúl Marticorena y Sandra Rodríguez Arribas
Título:	Blended Lerning: an experience with infographics an virtual laboratories using self-regulated learning
Congreso:	13th International technology, educations and development conference
Lugar:	Valencia
Fecha:	11, 12 y 13 de marzo de 2019

Tabla 3.6: Datos comunicación oral 2 en el congreso INTED 2019

Tipo:	Comunicación oral
Autores:	María Consuelo Sáiz Manzanares, María José Zaparaín, Sandra Rodríguez Arribas y Andrés Bustillo
Título:	Design of a smart art classroom in art history: a learning experience with Self-regulated serious games
Congreso:	13th International technology, educations and development conference
Lugar:	Valencia
Fecha:	11, 12 y 13 de marzo de 2019

Tabla 3.7: Datos comunicación oral 3 en el congreso INTED 2019

Tipo:	Comunicación oral
Autores:	María Consuelo Sáiz Manzanares, Sandra Rodríguez Arribas y Carlos Pardo Aguilar
Título:	Aprendizaje Autorregulado en Blockly games: un análisis de la efectividad de implementación en distintos entornos
Congreso:	IV Congreso nacional de psicología
Lugar:	Vitoria
Fecha:	22, 23 y 24 de julio de 2019

Tabla 3.8: Datos comunicación oral en el congreso nacional de psicología 2019

Tipo:	Ponencia invitada
Autores:	Sandra Rodríguez Arribas
Título:	Orientación personalizada al alumno/a en Moodle: Una propuesta a través del plug-in eOrientación
Congreso:	VI Congreso internacional en contextos psicológicos, educativos y de la salud
Lugar:	Almería
Fecha:	25, 26 y 27 de noviembre de 2020

Tabla 3.9: Datos ponencia en el congreso CICE 2020

Capítulo 4

Conclusiones

El uso de SRL y la gamificación dentro del aula, tanto en educación presencial, como en virtual o semipresencial, consiguen una alta satisfacción en el proceso de enseñanza-aprendizaje por parte del alumnado en todas las etapas educativas porque facilita el procesamiento de la información y homogeneiza las respuestas de aprendizaje entre los estudiantes [21, 44, 75, 77]. Además, si combinamos estas técnicas metodológicas activas con el uso de plataformas de *e-Learning* se facilita e incrementa el aprendizaje autorregulado y el rendimiento de los y las estudiantes [31, 82].

La utilización de estas metodologías educativas, ha demostrado ser muy efectiva en las materias de tipo STEM en la etapa educativa de Educación Primaria como proponía el objetivo **1a**, donde se ha podido comprobar que la motivación de los y las alumnas hacia estas asignaturas crece a través del empleo de talleres de gamificación [71] y aparece una mayor motivación para continuar su carrera profesional en alguno de estos campos.

Los *Learning Management Systems* facilitan la recopilación y análisis de datos, es decir, realizar lo que anteriormente se ha descrito como *Educational Data Mining* y cada vez son más utilizados en la Educación Superior [72]. Sin embargo, existen diferencias en relación con el uso de los recursos y actividades de Moodle entre estudiantes y profesores/as pueden, en parte, explicarse por un mayor número de profesores/as expertos en *e-Learning* en las titulaciones STEM [65] (objetivos **1b**, **2a** y **2b**). Este hecho es comprensible porque estas titulaciones han contado tradicionalmente con tecnologías que han facilitado la formación del profesorado. Por este motivo y como anteriormente se comentó, es fundamental continuar con la formación del profesorado en el uso de estas herramientas [30, 72] ya que las posibilidades que ofrecen los LMS para el proceso de enseñañza-aprendizaje son muchas y se siguen ampliando con cada actualización. Además, este aspecto resulta importante porque está relacionado con una necesidad detectada anteriormente y que la

Comisión Europea ha subrayado, relacionada con la importancia de tener en cuenta las competencias digitales de los profesores/as [30, 55].

Los profesores/as necesitan herramientas fáciles de usar que les ayuden a supervisar el proceso de aprendizaje y detectar a los alumnos/as en riesgo desde una fase temprana, como es la herramienta UBUMonitor empleada en distintos estudios llevados a cabo en los artículos de esta tesis [61, 72]. Esta detección permite a los profesores/as ofrecer una enseñanza más personalizada y ayudar a cada alumno/a que lo necesita cuando lo necesita como se planteaba en el objetivo **1c**. Por otro lado, combinar los resultados que nos proporcionan estas herramientas con otros análisis de datos empleando técnicas de minería de datos y análisis estadísticos tradicionales nos dará más información sobre los datos [69, 81].

El uso de la técnica de seguimiento ocular (*eye-tracking*) nos permite conocer el procesamiento de la información en distintos tipos de participantes durante la resolución de diferentes tareas [61, 68, 69] como indica el objetivo **1c**. El trabajo con esta tecnología abre muchos campos de investigación aplicada a numerosos entornos, uno de ellos es el de mejorar el estilo de aprendizaje y realizar propuestas de intervención personalizada según las necesidades observadas en cada estudiante aunque es un campo en el que no se utiliza ampliamente debido al coste de los equipos y al conocimiento previo que debe tener el profesorado para poder utilizarlo y analizar los datos recogidos [68].

Por todo esto se puede concluir que una enseñanza eficaz en la sociedad del siglo XXI requiere el empleo de diferentes recursos tecnológicos y formativos que deben ir de la mano para lograr un proceso de enseñanza-aprendizaje exitoso.

Capítulo 5

Líneas de trabajo futuras

El análisis de datos educativos, a pesar de ser un campo en el que se lleva investigando durante décadas, tiene todavía muchas posibilidades de investigación y mejora como se ha indicado en los artículos publicados que componen esta tesis doctoral y que abordan esta temática. Específicamente, se precisan más investigaciones en el campo de la enseñanza-aprendizaje en materias STEM en etapas educativas previas a la Educación Secundaria Obligatoria (Educación Infantil y Educación Primaria) para obtener un mayor volumen de datos que aumente la fiabilidad y la validez de los resultados de la investigación. El objetivo final es el de dar luz sobre las variables implicadas en la no elección en porcentajes semejantes de género de materias o titulaciones de corte STEM. Los resultados de estos trabajos de investigación facilitarán desarrollar acciones preventivas que permitan superar la brecha de género y garantizar la alfabetización digital global de la sociedad.

En este sentido, es importante tener en cuenta que las asignaturas STEM, en concreto las relacionadas con el aprendizaje de la programación informática en las etapas previas a la Educación Secundaria, no forman parte explícitamente de los planes de estudio en nuestro país. Este es un problema que también señalan otros estudios referenciados en los artículos que han servido de base para el desarrollo de esta tesis doctoral [21, 26, 29, 32, 52].

Otro de los aspectos en los que se debe seguir trabajando para ampliar los resultados hallados a través de la implementación de técnicas de EDM y LA es el análisis sobre la influencia de la utilización de los LMS por parte del estudiantado y el profesorado en otras universidades y centros educativos diferentes a la Universidad de Burgos. El objeto es el de comprobar la generalización de los resultados relativa a la influencia que tiene el uso del LMS por parte del profesorado sobre la utilización de los LMS en el estudiantado, resultado encontrado en el artículo publicado en la revista *Sustainability* [65]. Esta necesidad también se ha plasmado en otras investigaciones publicadas [3, 13, 59, 60, 62, 66]. Por este motivo en futuros trabajos de investigación se abordará el estudio de las motivaciones de los estudiantes en la elección de las titulaciones STEM frente a las NO-STEM. Además se analizará si la enseñanza en titulaciones STEM vs. NO-STEM y la modalidad de enseñanza están relacionadas con la utilización de determinados diseños didácticos [61, 65]. Asimismo, se estudiará si las competencias y el estilo de aprendizaje del estudiantado pueden influir en el proceso de enseñanza-aprendizaje.

Concretamente, los procesos de minería de datos al aplicar un método no supervisado como es el *clustering*, no permiten conocer el clúster perfecto, aquel en el que coinciden los grupos y las clases, si la muestra de datos no es muy amplia. Debido a ello, este aspecto se pondrá a prueba en nuevas investigaciones con muestras más amplias y heterogéneas de estudiantes que las disponibles para el artículo sobre seguimiento del aprendizaje de los alumnos/as en los sistemas de gestión del aprendizaje (LMS) [72].

Finalmente, en investigaciones futuras se profundizará en la utilización de la tecnología *eye-tracking* con el fin de obtener datos en participantes de otras etapas educativas diferentes a la educación de adultos y a la educación universitaria. En estos estudios se propondrá a los estudiantes la realización de diferentes tareas en distintas asignaturas. No obstante, hay que considerar que el uso de esta tecnología requiere un control muy exhaustivo del desarrollo de las tareas que debe ser aplicado en entornos de laboratorio, aspecto que dificulta el trabajo con las muestras amplias y aleatorias lo que supone un problema respecto de la generalización de los resultados [68,69,73].

Glosario

- **Árbol de decisión**: es una técnica de *machine learning* que permite analizar decisiones secuenciales basada en el uso de resultados y probabilidades asociadas. Permiten construir modelos predictivos basados en la clasificación según ciertas características, o en la regresión mediante la relación entre distintas variables para predecir el valor de otra.
- **Atributo**: en minería de datos es una propiedad o característica de una instancia. Una colección de atributos describe un objeto.
- **Blended-Learning**: es un enfoque de aprendizaje que combina la formación presencial y las actividades de aprendizaje en línea. La parte *online* de la formación no reemplaza las clases cara a cara con un profesor o profesora. Lo que se busca es incorporar la tecnología para mejorar la experiencia de aprendizaje y ampliar la comprensión de ciertos temas.
- **Clase**: en minería de datos, es el atributo discreto cuyo valor desea predecir en función de los valores de otros atributos. También se conoce como etiqueta.
- **Conjunto de datos**: en inglés *dataset*, es una colección de datos que contiene los valores para cada una de las variables que corresponden a cada miembro del conjunto de datos. Cada uno de estos valores se conoce con el nombre de dato. El conjunto de datos puede incluir datos para uno o más miembros en función de su número de filas.
- **Clustering**: es una técnica de minería de datos que permite agrupar datos en función de sus similitudes o diferencias. Es una técnica que se emplea generalmente con datos no etiquetados.
- **Estilos de aprendizaje**: son las condiciones educativas bajo las cuales un estudiante es más probable que aprenda. No se refieren a la información que aprenden, sino a cómo prefieren aprender los estudiantes y, en muchas ocasiones, a cómo les resulta más fácil aprender.

- **Estudiante en riesgo**: aquel que se considera que está en peligro de no alcanzar metas relacionadas con la educación (graduarse, aprobar la asignatura...).
- **Eye-tracking**: también conocido como seguimiento ocular, es el proceso de registrar y analizar los movimientos oculares de las personas para conocer los elementos que naturalmente llamaron su atención.
- **Instancia**: es cada uno de los datos de los que se disponen para hacer un análisis. Cada instancia, a su vez, está compuesta de características que la describen. En una hoja de cálculo, las instancias serían las filas; las características, las columnas.
- **Learning Analytics** (LA): es la medición, la recogida, el análisis y la presentación de datos sobre los alumnos/as y sus contextos, con el fin de comprender y optimizar el aprendizaje y los entornos en los que se produce.
- **Machine Learning**: es conocido en español como "aprendizaje automático". Es una subcategoria de inteligencia artificial (IA), que utiliza analisis por ordenador para analizar extensos conjuntos de datos y detectar tendencias relevantes. El ordenador aprende automáticamente los parámetros de los modelos a partir de los datos para pronosticar nueva informacion.
- **Minería de datos**: es un conjunto de técnicas y tecnologías que permiten explorar grandes bases de datos, con el objetivo de encontrar patrones repetitivos que expliquen el comportamiento de estos datos y, que estos, puedan ser utilizados para extraer conclusiones.
- **Moodle**: es el acrónimo en inglés de *Modular Object-Oriented Dynamic Learning Environment* (Entorno de Aprendizaje Dinámico Orientado a Objetos y Modular). Es un sistema de gestión de la enseñanza, diseñado para ayudar al profesor/a a crear fácilmente cursos en línea de calidad.
- **Online Project-based Learning** (OPBL): es un método de enseñanza en línea que propone convertir a los alumnos/as en los protagonistas de su propio aprendizaje, permitiéndoles seleccionar y estructurar la metodología de trabajo, mientras que los docentes se encargan de guiar y supervisar el proceso. Tiene el objetivo de que los estudiantes comprendan el valor real del conocimiento, además de permitirles aplicar la información obtenida en el plano práctico y así facilitar su entendimiento.

- **Selección de características**: es una técnica de aprendizaje automático que consiste en seleccionar una parte de los atributos de todos los datos a analizar, de modo que el modelo construido tenga una mínima tasa de error y una mayor capacidad de promoción.

- **Self-regulated Learning** (SRL): es un proceso cíclico en el que el alumno/a planifica una tarea, supervisa su rendimiento y luego reflexiona sobre el resultado. El ciclo se repite cuando el alumno/a utiliza la reflexión para ajustar y preparar la siguiente tarea.

- **Serious Games**: es una aplicación de la gamificación en el aula en la que los juegos son diseñados con un propósito formativo.

- **STEM**: es el acrónimo de los términos en inglés *Science, Technology, Engineering and Mathematics*, es decir, ciencia, tecnología, ingeniería y matemáticas.

- **Virtual Learning Enviroments** (VLE): es una plataforma en línea utilizada con fines educativos. Engloba todos los entornos en línea que actúan como complementos del curso, ya sean cursos en línea, recursos de lectura y sitios informativos con evaluaciones de habilidades independientes, u otras formas de aprendizaje virtual.

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