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Implementation of a Monitoring System for Students' Learning Paths

Rui Filipe Correia Ferreira

Masters in Computer Science and Business Management

Supervisor:
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Iscte

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October, 2023

TECNOLOGIAS
E ARQUITETURA

Department of Information Science and Technology

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"If we knew what it was we were doing, it would not be called research, would it?"

- Albert Einstein

Acknowledgments

This dissertation stands as a testament to the unconditional support from certain people, and to whom I extend my sincere and heartfelt gratitude.

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Resumo

As novas tecnologias revolucionaram o sistema educativo. Entre essas tecnologias, a utilização de sistemas de gestão da aprendizagem foi normalizada no ensino superior e trouxe muitas possibilidades para abordar os problemas atuais enfrentados pelos alunos e pelas escolas, tais como o aumento das taxas de abandono escolar, o fraco desempenho académico e a falta de motivação e envolvimento.

Nesta dissertação, analisamos o Moodle, o sistema de gestão de aprendizagem utilizado no Iscte, para encontrar os indicadores de percurso de aprendizagem que melhor podem representar os percursos de aprendizagem dos alunos para os visualizar e monitorizar. É feita uma análise da arquitetura do Moodle e dos indicadores do percurso de aprendizagem com o objetivo de desenvolver uma plataforma para apresentar esses indicadores. A plataforma consiste num *dashboard* em tempo real que extrai a informação do Moodle e a apresenta ao aluno, onde este pode escolher a unidade curricular que pretende para visualizar o seu percurso de aprendizagem. A validação da plataforma foi efetuada através de um questionário, onde 24 alunos matriculados no ensino superior responderam a questões sobre a sua familiaridade com sistemas de gestão de aprendizagem, bem como sobre o que acharam dos indicadores de aprendizagem propostos e da própria plataforma. Relativamente à sua opinião sobre a plataforma, 87,5% dos participantes consideram que a plataforma teria um impacto positivo no seu desempenho académico (20,8% concordam fortemente, enquanto 66,7% concordam)

Palavras-chave: Moodle, Indicadores do percurso de aprendizagem, Ensino superior, Aprendizagem auto-regulada

Abstract

New technologies revolutionized the educational system. Among those technologies, the use of learning management systems was normalized in higher education and brought a lot of possibilities to address current problems faced by students and schools, such as increasing drop-out rates, poor academic performance, and lack of motivation and engagement.

In this dissertation, we look at Moodle, the learning management system used at Iscte, to find the learning path indicators that can better represent the students' learning paths to visualize and monitor them. An analysis of Moodle's architecture and of the learning path indicators is made with the aim of developing a platform to showcase those indicators. The platform consists of a real-time dashboard that extracts the information from Moodle and showcases it to the student, where the student can choose what unit course they want to visualize their learning path.

The validation of the platform was performed with a questionnaire, where 24 students enrolled in higher education answered questions about their familiarity with learning management systems, as well as what they thought about the learning indicators proposed and the platform itself. Regarding their opinion on the platform, 87.5% of the participants think the platform would have a positive impact on their academic performance (20.8% strongly agree, while 66.7% agree).

Keywords: Moodle, Learning Path Indicators, Higher Education, Self-Regulated Learning

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Glossary of Acronyms

DOM	Document Object Model
EDM	Educational Data Mining
JSON	JavaScript Object Notation
LA	Learning Analytics
LMS	Learning Management Systems
NPM	Node Package Manager
PRISMA	Preferred Reporting Item for Systematic Reviews and Meta-Analyses
SAML	Security Assertion Markup Language
SQL	Structured Query Language
SRL	Self-Regulated Learning
UC	Unit Course

CHAPTER 1

1. Introduction

In the last decade, the educational sector has experienced a change due to the development of new technologies (Carrion, 2021; Pardo et al., 2017). It led to the creation of software systems like Learning Management Systems (LMS) that allow the universities to produce and store large amounts of data with analytical relevance to students' learning process and their needs (Amo et al., 2021; Erarslan & Şeker, 2021; Villalonga-Gómez & Mora-Cantallops, 2022). With the use of Educational Data Mining (EDM) and Learning Analytics (LA), the data students create by using LMSs can be used to improve the quality of learning, diminish dropout rates, and create predictive models for performance and identify at-risk students (Gaftandzhieva et al., 2022; Pardo et al., 2017). Furthermore, data generated by the student gives teachers an insight into their learning paths and processes to evaluate if students have met their learning objectives, allowing them to adapt courses based on student progress (Safsouf et al., 2021; Zafar et al., 2018). Learners' success is not directly connected to the number of learning resources or types of technology used in the learning process remaining now in the support learners have as well as their motivation and self-regulation (Yun et al., 2017). Furthermore, for LMS to work, students must be active in their learning process and interact with the system to develop their knowledge and skills (Villalonga-Gómez & Mora-Cantallops, 2022).

To reach deep levels of learning and long retention, students must achieve high levels of motivation in learning environments. (Bauer et al., 2020). To improve students' motivation, Self-Regulated Learning (SRL) strategies and gamification can be used (Yun et al., 2017; Zafar et al., 2018), for instance, SRL has been identified as a strong predictor of engagement and academic success (Erarslan & Şeker, 2021) as well as an enhancer of students' cognitive and metacognitive skills in addition to their motivation and engagement in learning environments (Gambo & Shakir, 2019). One of the methods to better understand students' use of SRL, is to perform an analysis of students' behavior in LMS (Rodriguez et al., 2021).

Moodle is an open-source cloud-based LMS centered on self-motivated mobile learning (Gambo & Shakir, 2019). Moodle was developed in 1999 and has over 316 million users worldwide, 1.8 billion course enrolments, 41 million courses in 42 different languages, and 179 thousand Moodle sites (Moodle, 2023). Millions of people use this platform as a toolbox to support their learning. Considering Moodle is open source, it is possible to develop tools and personalize them to the university's needs or to integrate Moodle with other applications. The learning interactions that Moodle provides for students to interact with their peers and teachers are through forums, feedback, collaboration, administrative panel, peer interaction, chats, and the ability to upload all learning resources needed (Gambo & Shakir, 2019).

This dissertation aims to identify indicators that can possibly quantify the learning path of students and implement the integration between a new platform and the LMS Moodle to visualize students' learning paths.

1.1. Motivation

Universities are looking for ways to increase student performance and the use of LMSs opens new possibilities and solutions. Teachers can have more insight into students' learning process, allowing them to make corrective changes to the courses when they identify a problem (Gaftandzhieva et al., 2022). To promote academic success, it is essential for teachers and universities to better understand students and their needs (Villalonga-Gómez & Mora-Cantallops, 2022).

Engaged students have increased involvement in the learning process, increased performance and productivity, and higher achievement rates (Erarslan & Şeker, 2021). Keeping students engaged and motivated is essential and online learning environments, such as Moodle (Gambo & Shakir, 2019), allows for the use of gamification and SRL techniques to assist students in defining learning objectives and reflect on their learning process, help learners to keep their motivation and engagement (Gambo & Shakir, 2019; Zafar et al., 2018).

Early prediction of students' academic performance might enable teachers to identify at-risk students and intervene in their learning process to reduce academic failure (Gaftandzhieva et al., 2022). Moreover, the display of students' information about their learning process through dashboards provides a better understanding of students' learning process and gives students the ability to visualize it (Safsouf et al., 2021).

Students react in different ways to the learning process. They might also interact in various ways with platforms like Moodle or other LMS, as not every student organizes the study and interacts with learning tools the same way (Villalonga-Gómez & Mora-Cantallops, 2022). In addition, students differ on the kind of learning materials they prefer to use the most, some prefer to use descriptive learning materials, while others prefer to use visual learning or collaborative learning materials (Kaiss et al., 2022). Even though there are different student profiles, it is difficult for teachers to understand each student profile and to guide students accordingly (Kaiss et al., 2022; Villalonga-Gómez & Mora-Cantallops, 2022).

Iscte started using Moodle as its LMS in the academic year of 2022-2023. Previously and for many years, Iscte used the Blackboard solution. This paradigm shift, with Moodle being an open-source LMS, enables integration with third-party software or the extraction of information generated by it. This was the main motivation to start this project, which aims to start developing an automated integration project to extract the digital footprint of students during their learning process while using Moodle and feed this data into a new platform to visualize the learning paths of students. Formerly, as it was not possible to explore the digital footprint of students using Blackboard, the only data that could be extracted was the performance of students in quests (e.g., quizzes marks) extracted from Blackboard as .csv files. Important indicators such as student downloads of contents, could not be retrieved at real-time to study students' behavior.

1.2. Objective

The objective of this dissertation is to plan, design and implement the integration between a new platform to display the learning path of students and the LMS Moodle to obtain data about the digital footprint of students in the LMS. The goal is to enable students to have a better insight into what their behavior is during the duration of a UC. It will show their learning path and digital footprint while using Moodle.

To monitor learning paths, it will be necessary to identify the indicators that are best suited to measure the dynamic behavior of students during the execution of a UC. Additionally, the goal is to study ways to quantify and visualize their learning path in a UC. To validate the indicators proposed, a questionnaire will be designed to test the new platform that will be developed. To be able to represent the real use of the platform, a set of mock data will be created to help visualize its real use.

To accomplish the objectives proposed, the dissertation aims to answer the following research questions:

- What are the indicators associated with the students' digital footprint in Moodle that can better measure their learning paths?
- How can we visualize students' learning paths during the UC with their digital footprint?

1.3. Methodology

The methodology used for the development of the platform in this dissertation is an agile software development model, composed of biweekly development cycles. Each cycle is composed by a set of five steps:

1. Requirements gathering – At the start of each cycle the requirements related to the functionalities to be developed are defined.
2. Design – The design phase comprises the design of the selected features to be developed in the cycle.
3. Development – Succeeding the design, the development of the features follows.
4. Tests – In this phase, tests are done by the developer, who has a higher insight into the features being tested. It includes tests performed individually on each feature, and tests performed on all the developed features.
5. Validation – This step includes the validation from the rest of the team involved in the project, verifying if the features developed delivered all the intended functionalities. If the step is a success a new cycle of development begins, and a new requirement gathering begins.

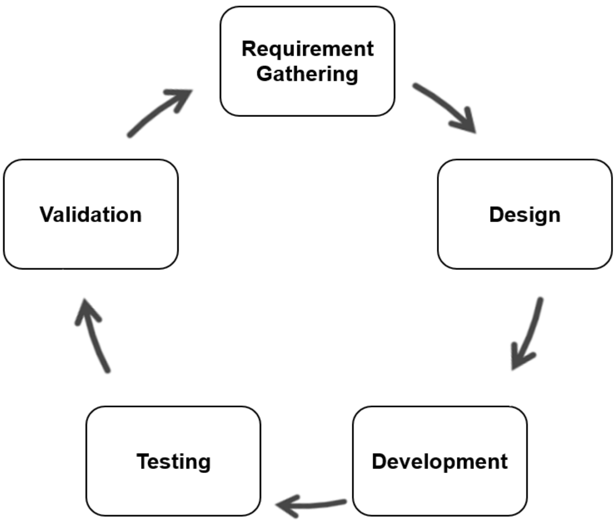


Figure 1.1 - LS2.0 Features Development Cycle

1.4. Dissertation Structure

This dissertation is structured as follows: Chapter 2 showcases the literature review, utilizing the PRISMA systematic literature review methods and the VOS viewer bibliometric visualization tool. Chapter 3 showcases Moodle's architecture and explores the data accessible within the platform. Chapter 4 addresses the definition of indicators to monitor students' learning paths. It showcases the definition of requisites to incorporate to design the features to visualize students' learning paths. Chapter 5 corresponds to the development and testing phase of the previously designed features to monitor and visualize students' learning paths. Chapter 6 showcases the validation of the proposed indicators and the platform through a questionnaire-based assessment. Finally, Chapter 7 describes the dissertation's conclusion and limitations, and gives insights into the future work.

CHAPTER 2

2. Literature Review

This chapter showcases the process of a systematic literature review. The use of LMS along with the data generated by it has been a topic of increased relevance and, consequently, there is a plethora of literature available. To filter the most relevant literature available for dissertations' themes, a systematic review of the literature was applied.

2.1. PRISMA Systematic Literature Review

The literature review methodology used in this dissertation is the Preferred Reporting Item for Systematic Reviews and Meta-Analyses (PRISMA). It is an evidence-based minimum set of items for reporting in systematic reviews and meta-analyses to either focus on the report of reviews evaluating the effects of interventions or as a basis to report systematic reviews with other objectives.

2.2. Keywords Identification

For the study selection, the first step is to identify keywords and create a search string to search the databases. It identified two search strings, one to access literature about the use of SRL, students' profiles, and their experiences during the use of an LMS, and the other to collect what are the indicators generated using LMS that the literature available considers most important. The collection of papers was made by inserting the following logical queries into the database:

Search String 1:

("Learning Management System" OR "Moodle") AND "data" AND "indicators" AND "Case Study"

Search String 2:

("E-Learning" OR "Gamification" OR "tutoring" OR "learning management Systems")
AND ("Self-regulated learning" OR "SRL")
AND ("Learning experience" OR "type of learners" OR "learner profile" OR "Student profile" OR "learning indicators")

2.3. Repositories

The search for papers was performed on the database Scopus. Elsevier Scopus is a database of peer-reviewed literature that hosts scientific journals, books, and conference proceedings. It is used by more than 3,000 academic government and corporate institutions.

2.4. Bibliometric Analysis

For the bibliometric analysis present in this paper, it was used the software Mendeley. The use of this software gave the possibility to extract bibliometric data like the name of the authors, year of publication, type of paper (conference paper or journal paper), the number of citations, the title, the abstract, and the keywords of the respective papers.

2.5. Bibliometric Research Tool

In this dissertation, we use the VOSviewer research tool for network analysis allowing us to visualize bibliometric networks of the papers present in the sample. The construction of the networks is based on the title and abstract, the authors, and the keywords of the respective papers.

2.6. Literature Review Results

2.6.1. Prisma Flow Diagram

The PRISMA flow diagram in Figure 2.1 illustrates the process of study selection in the systematic literature review. The search of the query in the database Scopus resulted in a sample of 78 studies in the established timeline of October 2022.

After analyzing the abstract of the studies that were extracted from Scopus, it was made the exclusion of 56 studies due to the abstracts not corresponding to the alignment of this paper. Of the studies left, two could not be retrieved. The rest of the studies were submitted to a full-text analysis that led to a final exclusion of two studies that did not correspond to the content of the abstract and was not useful for the analysis. The final number of studies selected was 18 studies.

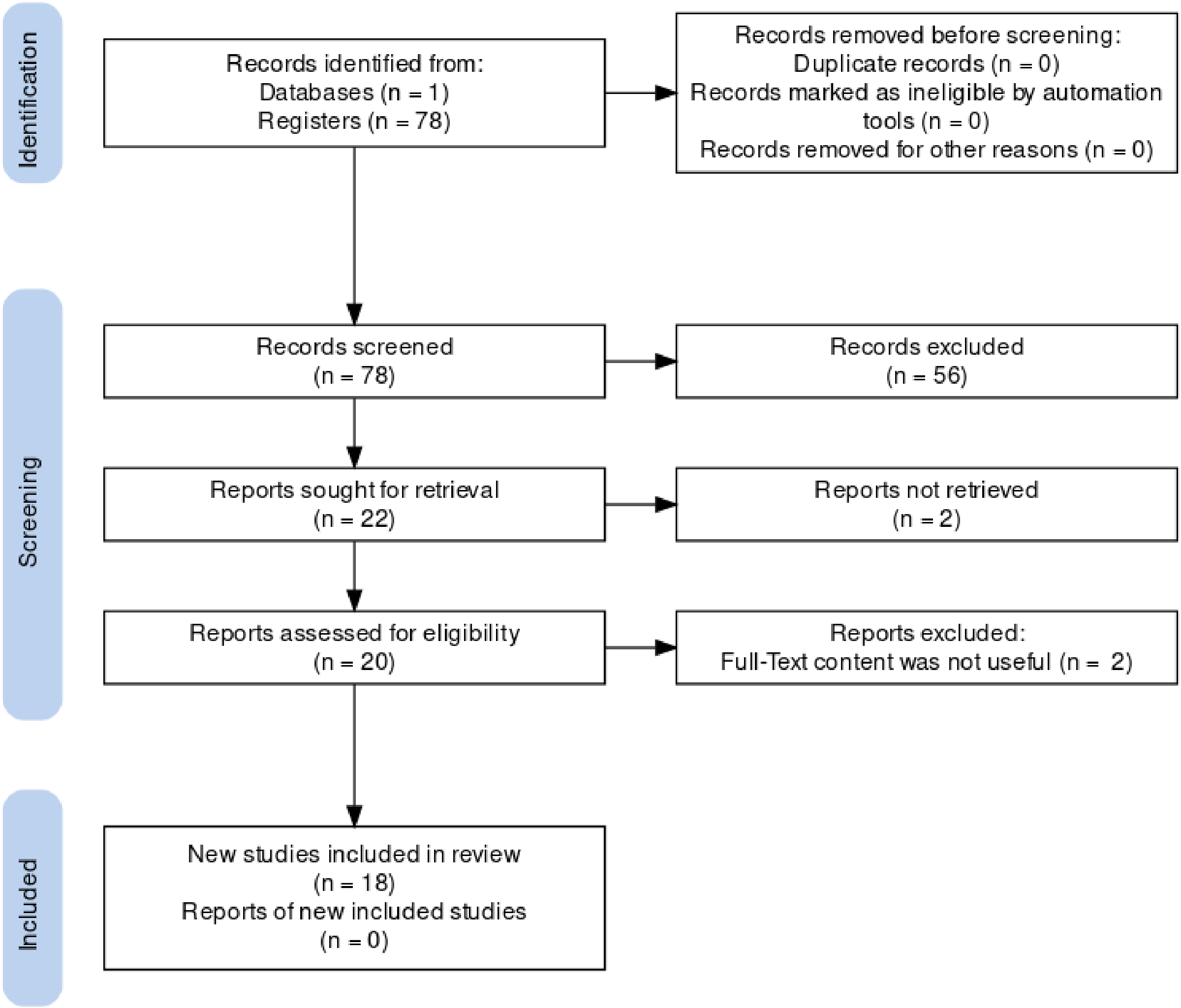


Figure 2.1 - PRISMA methodology flow diagram

2.6.2. Papers With Full-Text Reading

According to the established systematic literature review in the last sub-chapter, a sample of 18 papers was collected and subjected to a full-text reading and analysis. Table 2.1 represents a list of the sampled papers and the corresponding methods used to analyze the students' information. It is important to note that three of the papers are literature reviews and do not work over data directly extracted from the students.

Table 2.1 - PRISMA Literature Review Results

ID	Title	Reference	Method
1	Profiling distance learners in TEL environments: a hierarchical cluster analysis	Villalonga-Gómez & Mora-Cantallops, 2022	Hierarchical Cluster Analysis
2	Exploring Online Activities to Predict the Final Grade of Student	Gaftandzhieva et al., 2022	Random Forest, XGBoost, KNN, SVM, and Statistical Analyses
3	Towards a Model of Self-regulated e-learning and Personalization of Resources	Kaiss et al., 2022	Literature Review
4	Experimental Design of Learning Analysis Dashboards for Teachers and Learners	Safsouf et al., 2021	Statistical Analyses
5	Factors Influencing College Students' Teaching, Social, and Cognitive Presence in Online Learning: Based on a National Survey	Xu et al., 2021	Statistical Analyses and Regression Model
6	A privacy-oriented local web learning analytics javascript library with a configurable schema to analyze any edtech log: Moodle’s case study	Amo et al., 2021	Statistical Analyses
7	Investigating e-learning motivational strategies of higher education learners against online distractors	Erarslan & Şeker, 2021	Statistical Analyses
8	Interactions between learner’s beliefs, behaviour and environment in online learning: Path analysis	Abouzeid et al., 2021	Statistical Analyses
9	Using clickstream data mining techniques to understand and support first-generation college students in an online chemistry course	Rodriguez et al., 2021	K-Means Clustering

10	How effective are online teaching activities? A use case study in Higher Education	Carrion, 2021	Statistical Analyses
11	Evaluation of learning motivation within an adaptive e-learning platform for engineering science	Bauer et al., 2020	Statistical Analyses
12	Fostering Evidence-Based Education with Learning Analytics: Capturing Teaching-Learning Cases from Log Data	Kuromiya et al., 2020	Statistical Analyses
13	New development and evaluation model for self-regulated smart learning environment in higher education	Gambo & Shakir, 2019	Smart Learning Environment Pedagogical and Educational Requirements Mode
14	Gamifying higher education: Enhancing learning with Mobile Game App	Zafar et al., 2018	Statistical Analyses
15	Practicing the Scholarship of Teaching and Learning with Classroom Learning Analytics	Alizadeh, 2018	Statistical Analyses
16	Improving a mobile learning companion for self-regulated learning using sensors	Yun et al., 2017b	Literature Review
17	Modeling a Seamless Learning framework in higher education	Chin et al., 2017	Literature Review
18	Combining University student self-regulated learning indicators and engagement with online learning events to Predict Academic Performance	Pardo et al., 2017	Cluster Analysis, One-Way ANOVA, Multiple Regression Analysis

2.6.3. Identification of Research Themes

The papers identified were focused on different areas of the dissertation subject of study. Table 2.2 shows the various themes of research addressed by the papers. As it shows, SRL is the theme most discussed in the papers as it was referenced in every paper but two. Followed by EDM/LA, Learning Experience, Learning Activities, and LMS Log Data that are also explored in the papers' sample.

Table 2.2 - Literature Review by Research Themes

	Paper ID																		
Research Themes	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**Total**
Student Profiling	X		X						X										3
Blended Learning	X											X		X	X			X	5
Metacognitive Skills	X		X															X	3
Motivation Indicators	X						X				X			X	X			X	6
SRL	X	X	X	X	X	X	X	X	X	X	X		X	X		X	X	X	16
Performance Prediction		X					X	X	X									X	5
LMS Log Data		X	X	X		X				X		X				X		X	8
EDM/LA		X	X	X		X		X		X		X			X	X		X	10
Dashboards			X	X		X						X							4
Learning Experience	X				X					X	X	X	X		X	X		X	9
Moodle		X		X		X	X			X		X	X						7
Learning Activities				X		X	X			X	X			X	X			X	8
Clickstream Data								X											1
Gamification														X					1
Scholarship of Teaching and Learning															X				1

2.7. Network Analysis and Visualization

Figure 2.2 shows the most frequent keywords used in the titles and abstracts of the papers present in the sample. The analysis was made using a full counting method, with a minimum number of occurrences of each keyword of three. It identified 13 keywords that were selected for the analysis. In Figure 2-2, we found three clusters, with 13 items, 60 links, and a total link strength of 130. The first cluster is represented by green, where the largest node is located, corresponding to self-regulated learning, the second cluster corresponds to learning analytics which is represented in red, and the third cluster corresponds to computer-aided instruction which is represented in blue.

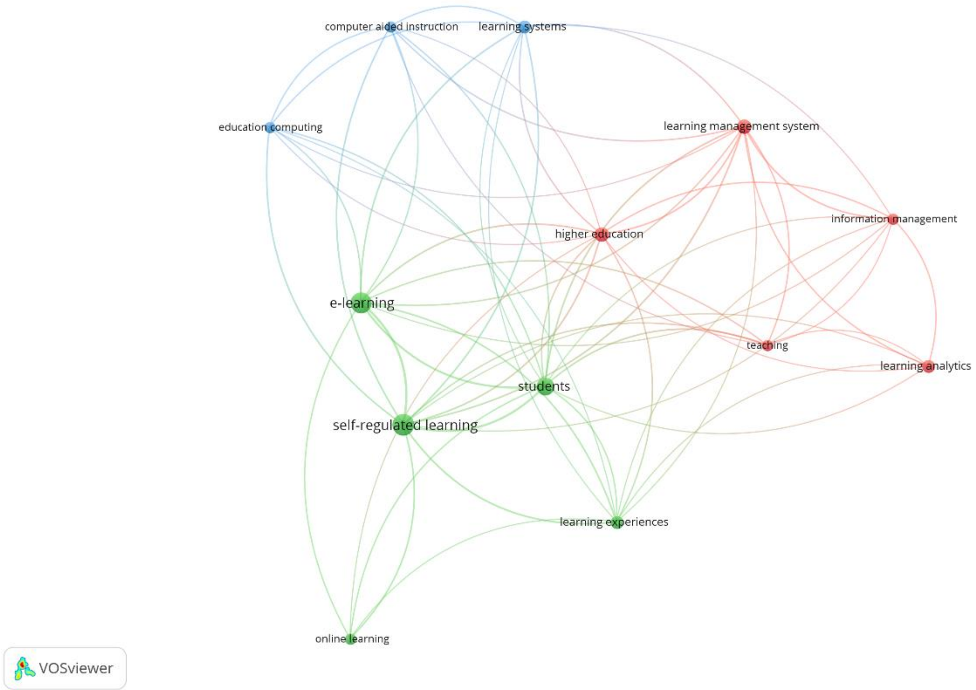


Figure 2.2 - Network Visualization of Keywords Occurrences

In figure 2.3 we also analyzed the term co-occurrences on the sample of papers. It used a full counting method with a minimum number of occurrences of five times. The analysis resulted in 28 terms. The analysis was conducted with the 20 most relevant terms and resulted in the creation of three clusters, with 120 links and a link strength of 1537. The first cluster, shown in red, represents the theme of the learning experience; the second cluster, shown in green, represents the theme of educational data analysis; and, finally, the third cluster, shown in blue, represents the theme of smart learning environments.

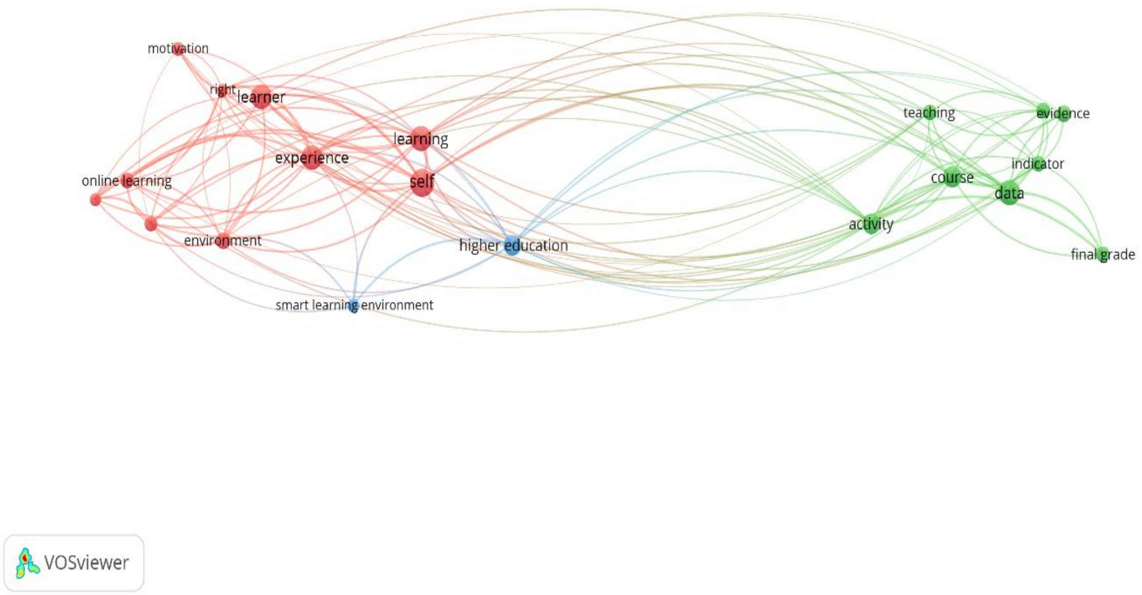


Figure 2.3 - Title and Abstract Keywords Co-Occurrences Network Visualization

At last, in Figure 2.4, we analyzed the co-authorship type of analysis using the full counting method. Resulting in 58 authors, with 17 clusters, 93 links, and a total link strength of 94.

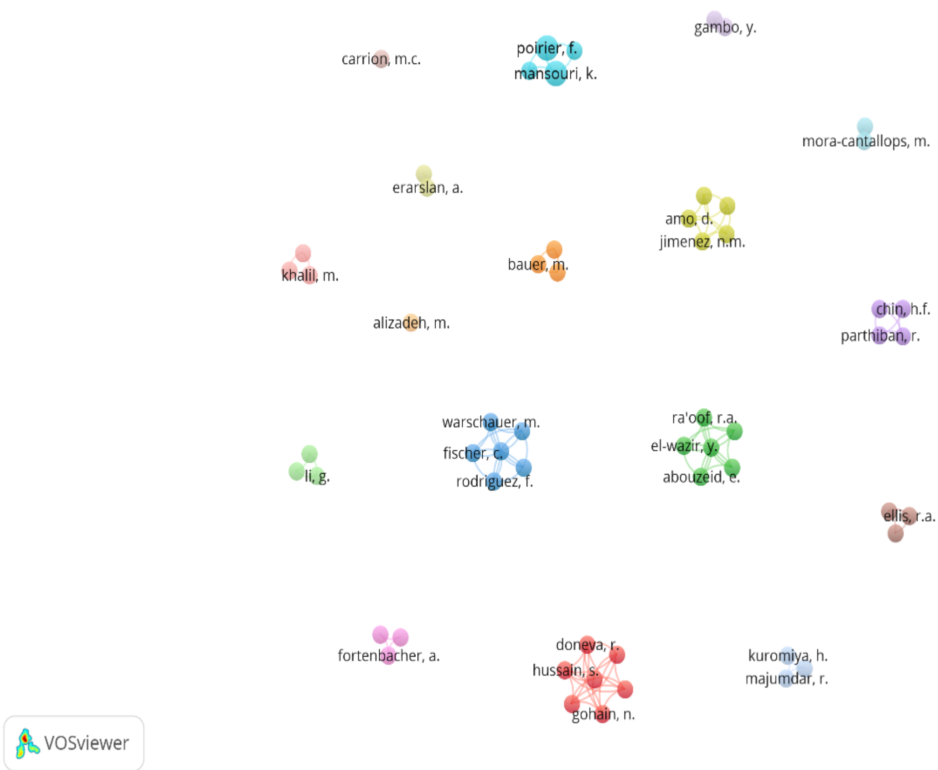


Figure 2.4 - Author and Co-Author Network Visualization

2.8. Results Synthesis

In Table 2.3, the list of the most important papers with their respective contributions was listed.

Table 2.3 - Most important papers with their contributions

Reference	Title	Contributions
Rodriguez et al., 2021	Using clickstream data mining techniques to understand and support first-generation college students in an online chemistry course	Four different types of students (based on their participation): Early Planners, Planners, Procrastinators, and Low engagement. Behavior while using LMS differs depending on the student.
Safsouf et al., 2021	Experimental Design of Learning Analysis Dashboards for Teachers and Learners	Use of dashboards and visualization of students learning paths increases their engagement and success rate.
Kuromiya et al., 2020	Fostering Evidence-Based Education with Learning Analytics: Capturing Teaching-Learning Cases from Log Data	It is possible to use LMS data to make interventions in the learning process.
Kaiss et al., 2022	Towards a Model of Self-regulated e-learning and Personalization of Resources	Students might interact in different ways depending on the type of content they access, i.e., if they access descriptive or visual content and so on. Students should be provided feedback on their performance
Amo et al., 2021	A privacy-oriented local web learning analytics JavaScript library with a configurable schema to analyze any edtech log: Moodle's case study	LMS log data enables the visualization of the learning process and extracts the number of interactions that occurred.
Pardo et al., 2017	Combining University student self-regulated learning indicators and engagement with online learning events to Predict Academic Performance	Predicting students' performance through their Learning Events. Learning Events include access to course notes, resources, videos, and different types of exercises.
Gaftandzhieva et al., 2022	Exploring Online Activities to Predict the Final Grade of Student	There is a correlation between final grades and students' online activity and class attendance.

The most significant contributions extracted from the literature review were about either the students' digital footprint or their learning path.

These studies helped identify what are the most important indicators that can be extracted from the LMS to visualize and analyze students' learning paths. The data extracted from the LMS differs depending on the objective of the analysis.

Rodriguez et al., 2021 identified that there are four types of students according to their participation during the duration of a UC. The type of students identified were: Early Planners, Planners, procrastinators, and Low Engagement students. It was identified that access to learning content differs among the different types of students. While the Early Planners and Planners have consistent access to the learning content, the Procrastinators students access the learning contents at the end of the UC. Even though the Low Engagement students also increase their access to the learning contents at the end of the UC, they do it at a lower rate than the Procrastinators. Early Planners have been identified to have higher grades and Low Engagement to have the lowest, showing how the SRL impacts students' success. It was extracted from the LMS data about every time students access videos from the learning material so it can be made an analysis of the time when their activity happens. Kaiss et al., 2022 identified that other than the students' engagement and participation, they can also be separated into different groups looking at what kind of learning content they access. Some students prefer to access content with a higher descriptive nature, while others prefer to access content with a higher visual nature. Identifying that different students have different needs helps promote their use of SRL methodologies. To obtain this information, it was extracted from the LMS the data about the type of activity that the student accessed, dividing it into three categories: descriptive learning content, visual learning content, and collaborative learning content. Moreover, Kuromiya et al., 2020 developed a tool to intervene in the learning process using LMS log data to have a real-time intervention system to help assist students and teachers during the UC. As the data extracted from the LMS needs context, it was extracted information about the course itself too, such as class size, the subject, the course, and the grades. The rest of the information taken for the project was made in the tool developed, where they would fill a form with the problem they found, the intervention they want, with date and title of the intervention, the type of control of the intervention, with date and title of the type of control, and the results of the intervention made to the various students.

The creation of dashboards with information from the students' behavior on the LMS has been made by various papers present in the sample to analyze their learning path. Safsouf et al., 2021 developed learning analytic dashboards to report data about students during their learning process. It has two views, one for the students and the other for teachers. The teachers' view has a feature that identifies students that are at risk of dropout. The data that the tool extracts from the LMS for the creation of the dashboards represent the information of the course itself, including name, number of total activities, number of students, and number of sections planned for the course; the participation of the student on the learning activities during the course such as exercises, assignments, quizzes, among others. After the extraction, the data can be worked to create new information such as the progression of the student on the course, and the number of activities he completed compared to the total number of activities. It is essential that students receive feedback on the learning process, and it can be done through messages or the visualization of their learning process. In addition, Amo et al., 2021 developed a learning tool that enables students and teachers to visualize students' interactions with their tasks. It shows how many times they interacted with the learning contents as well as a dashboard that enables them to see the history of their interactions, i.e., it lets students visualize how their interactions in their learning process were spread during the UC. The analysis is made for the day of the week, and month and it also saves the last time the student has logged in. For it to be possible it is needed to extract what type of activity the student performs during his use of LMS each time he does something as well as the time and the date.

Both Pardo et al., 2017 and Gaftandzhieva et al., 2022 developed performance predictive models based on the students' online learning activities, identifying that, students' interaction with learning events such as online activities, correlates with their overall academic results. Gaftandzhieva et al., 2022 identified the readiness of the students, i.e., if the student delivers their assignments before or after the deadline and how much earlier they do it. It also compared the difference between their first grades and their final grade to see how effective the study was, and it showed a positive result. Pardo et al., 2017 use the different types of activities performed by the student to perform the predictive model.

In every paper, it can be identified that the different types of activity and the number of times the student participates in them are essential for any kind of analysis or visual representation. Other variables that can be important to include are the information about the UC itself, as depending on study, different types of activities might have different effects and generate different needs in the student. When identifying different types of students and developing dashboards it is important to register the time at which the students participate in the learning process. When possible, the extraction and use of lecture attendance in the analysis is important as it correlates with the students' performance and engagement. With this in mind, we can identify that students' learning paths can be visualized using data extracted from the logs of the LMS.

Moreover, the use of SRL strategies is a recurrent theme in the papers as its methodologies improve students' learning. Engagement and motivation, when evaluated and represented visually in the various papers, are shown to be increased by self-regulated learning techniques. For example, when Rodriguez et al., 2021 identified the different types of students, the ones that early planned and accessed the learning contents throughout the duration of the UC were considered to have better SRL skills as they are connected to setting goals and planning the learning process accordingly.

CHAPTER 3

3. Moodle Architecture

In this chapter, we will delve into Moodle's architecture, gaining insights into its fundamental structure and composition. We will begin with a comprehensive analysis of Moodle's architecture, exploring its various layers and the programming languages in which it is developed. Furthermore, our analysis will then extend to the core of Moodle's data storage, where we will find what specific information resides within its database and how it can potentially be extracted so it is possible to know what information is available to use as learning indicators.

3.1. Moodle Architecture

Moodle is an open-source software that supports and helps manage the learning process of students. It is a web-based application written mainly in PHP that follows a modular and flexible architecture. At its core, Moodle can be divided into three architecture layers (Moodle Architecture, 2023; Analytics API, 2023).

The presentation layer consists of its interface and enables user interactions. It is a web-based interface that allows users to participate in the plethora of features Moodle offers such as accessing course materials, participation in discussions, submit assignments, solve quizzes, and overall engage in different learning activities. The interface is made to be used both for computers and mobile devices with customizable, intuitive, and responsive layouts.

The application layer accommodates the core functionalities available in Moodle serving as the intermediary between the other two layers. It enables the installation of plugins and modules to the current installation to add and customize functionalities. Examples of functionalities that are made in this layer include the authentication of users, management of courses, use of assessment tools, and collaboration features. The primary functionalities present in courses are provided by modules that can be installed. In the standard Moodle installation, there are some modules already provided such as quizzes, forums, assignments, resources, wiki, lessons, glossary, and so on.

Finally, the data layer which includes the database management system is used to both store and access data generated. During its installation, Moodle enables the client to choose between multiple SQL (Structured Query Language) based options, such as MySQL, MariaDB, PostgreSQL, and Microsoft SQL Server. This database stores data such as user profiles, course information, learning activities information, grades, and user logs, among other important data.

Furthermore, Moodle follows a plugin-based architecture to allow the customization of each Moodle installation. It is possible for developers to develop plugins, either for functional purposes or to enhance and change Moodle's appearance. This system enables clients to easily personalize their installation to fulfill their needs. Moodle's architecture clearly prioritizes the ability to personalize the product to the needs of the client, enabling them to empower both learning and teaching activities while giving administrators the capability to customize and manage it according to their goals.

Iscte is going to use Moodle 4.0 version in the academic year of 2023-2024 so, to integrate it with LS, the architecture studied corresponds to this version. It is important to note that Iscte's Moodle installation does not have any plug-in or change made that would affect the data available for the analysis of students' learning paths hence the integration with LS would be possible with other Moodle installations that have the standard 4.0 version.

This was the version of Moodle studied to retrieve all the information needed to monitor and visualize students' learning paths. Its architecture is complex and has the information displayed in different places with complex connections. The database of this version has 469 tables. Even though all the information is gathered in different places and with a lot of connections that are complex to establish and understand, it also has an API incorporated to help the process of extracting the information. The API is called "Web Service" and it has some functions that help retrieve the information needed, but not every information can be retrieved by the API, leaving the need to directly access it from the database.

Iscte's Moodle has sensitive information that cannot be accessed by everyone and if in any case it would be deleted or altered would cause great damage to the institution. To prevent any misfortune to happen, it was explored the option of creating Stored Procedures, leaving the access of the information secure and controlled with only the ability to read certain parts of the database while the rest of the information would be secure without any risk of being accessed without permission. All the interactions with Moodle will be one way, i.e., it will only be read operations, not write, update, or delete as the aim of this thesis is to extract learning indicators within the information that Moodle generates during the students learning process to visualize and monitor each student learning path, and not to change any information that Moodle is storing in its database.

Such alterations to Moodle's database such as the addition of Stored Procedures can be made directly into it and do not affect the rest of the platform, only the ability to extract information kept on it. Moodle itself will not suffer any kind of change to its architecture or features.

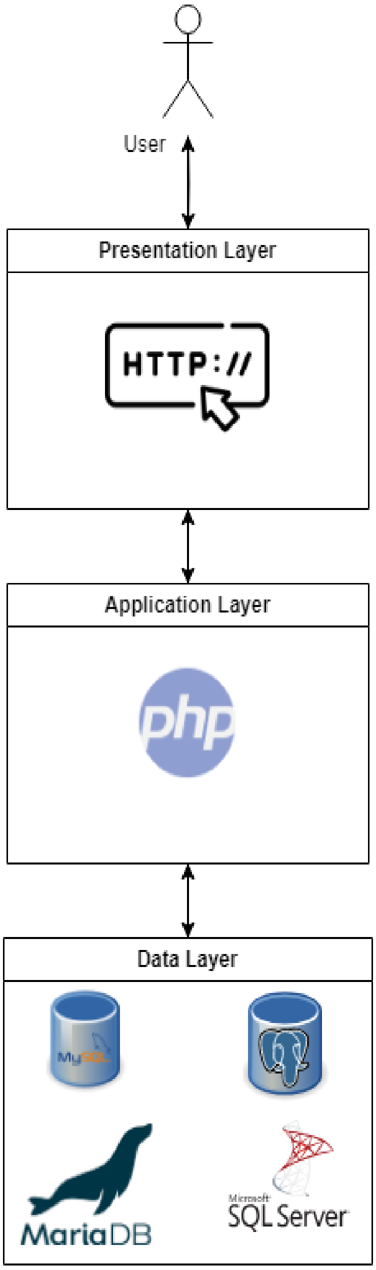


Figure 3.1 – Moodle Architecture Schema

3.2. Moodle's Stored Data

To explore potential indicators that can be derived from Moodle, an in-depth analysis of its database was conducted. This investigation aimed to identify the wide range of information stored by Moodle during students' learning journeys. Moodle's database is very complex, housing a vast amount of information. Notably, Moodle 4.0. has 469 tables dedicated to storing all the information related to courses and enrolled students.

In Moodle, each curricular unit corresponds to a distinct course, and student interactions are limited to the courses in which they are officially enrolled at. As information derived from the learning paths indicators will be utilized on a per-course basis, ensuring that it remains segregated and exclusive to each respective course, without any sharing of data of the students' behavior between courses, having the identification of to what curricular unit the student actions and learning materials belong to is indispensable and Moodle stores that information. It is also important to identify the corresponding student for the information stored, in cases where the information is associated with a particular student.

Additionally, all learning materials that teachers publish for each Moodle course are stored in a database and can be categorized into the following sixteen categories: Files, URLs, Pages, Books, Forums, Assignments, Quizzes, Surveys, Choices, Glossaries, Wikis, Chat, Database, Lessons, Workshops, SCORM.

Even though Moodle utilizes these categories, it does not inherently possess the capability to distinguish the specific meaning of each learning material. For instance, if a teacher uploads two learning materials under the category of "File," Moodle itself cannot automatically differentiate between them, such as identifying whether one material corresponds to lecture slides while the other relates to exercise content from a specific syllabus.

To address this limitation, Moodle offers a tagging feature, which gives the ability to teachers assign tags to the learning materials they publish. Among the lines of the previous example, the teacher could tag one of the Files as "Slides" and the other as "Exercises," thereby providing a means to distinguish the content more effectively. Figure 3.2 gives a visual representation of how the tagging feature works on Moodle's database. When a student access one learning content, the log shows what is the context of that interaction. This context provides us with the tag that is associated with the learning content accessed, providing the tag's name, and enabling the distinction between learning contents that have the same Moodle category but different contents, like it was illustrated in the previous example.

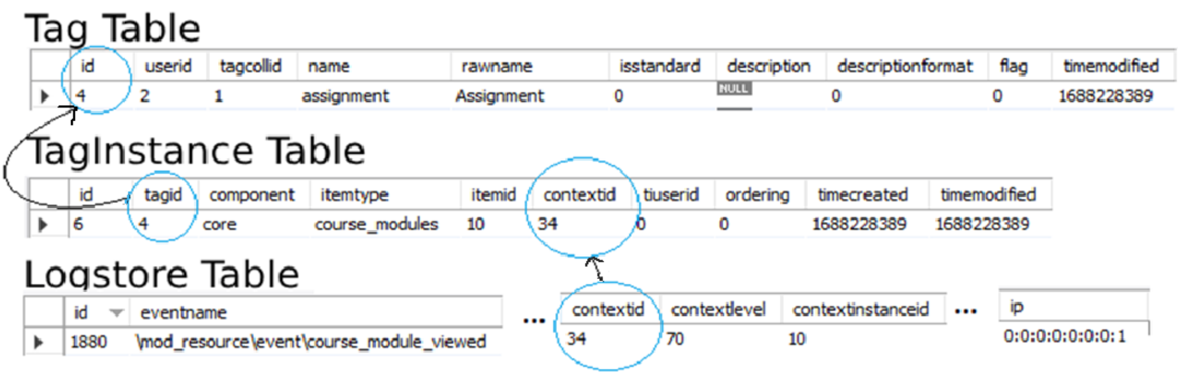


Figure 3.2 – Connection Between Tags and Logs in Moodle's Database

To recognize students' behavior during their learning process, one of the most critical datasets that Moodle retains is the logs. Each log entry contains vital information, including the user to whom it belongs to, the corresponding course where the action occurred, the timestamp, the object with which the user interacted, and the type of interaction (read, write, update, or delete). Fundamentally the logs store every single interaction that students have with Moodle, giving the ability to identify where the interaction occurred, the time it was done, and who it belongs to. These logs play a pivotal role in gaining insights into students' activities and engagements within the Moodle platform. Figure 3.3 showcases an example of the *logstore* table most important fields used for the analysis.

Logstore Table

id	action	target	objectable	object_id	crud	edulevel	contextid	contextlevel	contextinstanceid	userid	courseid	timecreated
1817	viewed	course_module	resource	1	r	2	21	70	3	3	2	1688313212

Figure 3.3 – Example of the most important fields in a line of the Logstore Table

In addition to logs, all the information resulting from student actions is stored in their dedicated sections of the database. For instance, when a student attempts a quiz, the relevant data is saved in their personal table, which maintains records of all quiz attempts made by each student across different quizzes with all the information relevant to the attempt, while at the logs table it only stores that the student attempted the quiz. This database structure and interaction is consistent throughout the platform and is organized the same way in other learning contents, including assignments and their submissions, forums and their posts, and other interactive elements. Figure 3.4 exemplifies the how Moodle stores information about both quizzes and their attempts.

Essentially, each student's data remains segregated, ensuring that their individual learning progress and interactions are efficiently tracked and managed within the Moodle platform.

Quiz Table

id	course	name	...	attemptonlast	grademethod	decimalpoints	...	sumgrades	grade	timecreated	timecheckstate	sumgrades	gradednotificationsenttime
1	2	Quiz 1		0	1	2		3.00000	10.00000	1679604675	NULL	2.00000	1679609023

QuizAttempts Table

id	quiz	userid	attempt	uniqueid	layout	currentpage	preview	state	timestart	timefinish	...	timecheckstate	sumgrades	gradednotificationsenttime
1	1	3	1	1	1,0,2,0,3,0	2	0	finished	1679609007	1679609023		NULL	2.00000	1679609023

Figure 3.4 – Example of Moodle's Quiz Attempts Storage

CHAPTER

4. Learning Path Indicators

In this chapter, we will explore the definition learning path indicators and their crucial role in assessing students' progress and learning experiences within the Moodle platform. Learning path indicators are key metrics that offer valuable insights into how students engage with their educational journey.

Throughout this chapter, we will take a closer look at the different types of learning path indicators and how they are applied to monitor and visualize students' learning paths. By understanding the purpose of these indicators and their relevance within the complexity of Moodle's data system, our aim is to establish a solid foundation for effectively tracking and visualizing students' unique learning paths.

4.1. Identifying Learning Path Indicators

The identification of indicators for learning paths was accomplished through a comprehensive approach, drawing insights from diverse sources. This process involved a thorough analysis of the current state of research, where existing literature on LA, EDM, and previous use cases provided valuable insights. These sources revealed indicators that had been employed to assess student progress, forming the foundational basis for the indicators obtained in this study.

Additionally, significant indicators were derived from Moodle itself, which employs LA for the development of an ongoing student risk-detection system that is still in the developmental phase (Students at Risk of Dropping Out, 2023; Analytics API, 2023). This system has not yet been fully implemented. This analysis led to the identification of three distinct categories of learning indicators, which will be elaborated upon further. It is important to note that these three categories were made to organize them into their main goal but, all the indicators might give information about other aspect of the learning path, for instance, if a student participates on a forum, it shows both engagement on the subject and social interaction with its peers.

Providing students with the capability to compare their indicators alongside those of their peers within the same UC holds significant importance. This comparative analysis offers students a valuable perspective on their engagement and performance throughout the semester in relation to the average student within the UC. Beyond individual insights, such comparisons develop a sense of competition among students, motivating them to maintain active engagement and participation throughout the course. This dynamic not only empowers students to measure their progress more effectively but also encourages a collective drive to stay on par or exceed the class average, enhancing overall engagement levels within the UC.

4.1.1. Engagement Indicators

Engagement indicators constitute a vital category to understand the students' learning path, providing a fundamental framework to evaluate the dynamic interactions and participatory behaviors displayed by students within the educational environment. These indicators are crucial for understanding the extent and quality of students' involvement with learning materials, activities, and resources, provide essential insights into the overall process of studying and skill acquisition.

In the context of this research, engagement indicators are highly important as they provide a mean to carefully examine students' engagement patterns and preferences. These indicators encompass a spectrum of metrics that encapsulate the scope, intensity, and diversity of students' interactions with Moodle.

One of the engagement indicators manifests in the frequency with which students interact with distinct content genres, such as reading lecture materials, doing exercises, attempting quizzes, participating on forums, and working on their assignments. This measurement of frequent interaction reveals students' preferences, shedding light on the academic aspects that consistently capture their interest.

Furthermore, another salient indicator introduces a temporal dimension to the analysis of student interactions. This temporal metric searches into the chronology of interactions throughout the academic semester, presenting insights into the rhythm of students' learning process. By monitoring interaction frequency on a weekly basis, this metric gives insight into the frequency with which students engage with Moodle's content over a span of time. Overall, this indicator gives a deep understanding on the students' engagement patterns, spotlighting trends and oscillations that may align with curricular progression, assessment deadlines, or other contextual triggers.

Finally, another engagement indicator was established that examines the alignment between the delivery date of assignments and their stipulated deadlines. This metric delineates whether a student's submission adheres to the designated deadline, shedding light on the punctuality of their submissions. This comparative assessment reveals a spectrum ranging from punctual deliveries, early submissions, to instances of late submission after the deadline. This indicator thus contributes to an assessment of the students' time management and responsiveness to assignment deadlines.

Table 4.1 – Engagement Indicators Overview

Name	Formula	Description
Content Accessed by Week	The sum of the accesses divided by each semester week	The number of times a student accesses or interacts with learning contents on Moodle each week of the semester
Content Accessed by Type	The sum of the Accesses divided by each content type	The number of times a student accesses or interacts with each type of learning content on Moodle. The types are: Lecture Materials, Exercises, Quizzes, Forums, and Assignments.
Assignment Delivery Delay	Deadline – delivery date	The number of days a student delivered the assignment before, or after the deadline.

4.1.2. Cognitive Indicators

Cognitive indicators are significant to establish the learning path of students. They form a crucial framework that helps us understand how students engage with their cognitive abilities and make progress in their studies. These indicators showcase how students interact with learning materials, tasks, and resources, providing valuable insights into their intellectual growth and skill development. They offer a way to analyze the finer details of how students think and learn. These indicators cover various aspects, giving us a view of the breadth, speed, and variety of cognitive interactions students have within the Moodle environment.

One standout indicator is the grades of all the attempts made in a quiz by the student. It is a key tool for uncovering how well students grasp subject matter. It also helps giving a broader understanding of how students developed their knowledge through the analysis of their history of attempts on a specific quiz.

The velocity in which students manage to learn is another important measure. It tells us how quickly students reach their peak performance, giving us a sense of their adaptability and learning speed.

Among these cognitive indicators, best grade a student manages to get is particularly significant. It showcases the highest level of cognitive achievement. Another informative metric is Consolidation, which reveals how often students attempt quizzes. This metric gives insight into how deeply students engage with content and how they refine their understanding.

Exploring the Average Time spent on each quiz adds another layer. It reveals the pace at which students engage with cognitive material, showing their thoughtful learning approach. Extending this framework, diving into the History of Attempts gives us a story of cognitive progress. It tracks the learning journey through multiple attempts, showing how cognitive skills evolve over time.

Through this comprehensive exploration of cognitive indicators, we gain a deeper understanding of how students engage intellectually and grow throughout the learning process. The monitoring of all the indicators at the same time gives us a good overall image of the possible difficulties the student faces as well as the dedication he grants the subject.

Table 4.2 –Cognitive Indicators Overview

Name	**Formula**	**Description**
Best Quiz Grade	Max quiz grade	The best grade a student managed to get on each specific quiz.
Learning Speed	Min attempt where grade = 100%	The first attempt in which the student manages to get the maximum grade (100%) in each quiz.
Consolidation	Total number of attempts made	The total number of attempts a student makes in each quiz.
Learning Progression	All the attempts made with the respective grades	For each quiz, the history of attempts a student makes. Showcases the grade and the attempt number.
Average Time Spent	Avg (finish time – start time)	The average time a student manages to finish each quiz attempt in each quiz.

4.1.3. Social Indicators

In the context of understanding students' learning paths, social indicators help us understand how students interact within the educational environment. These indicators are tools that give us important information about how often students interact with each other. They give us a way to closely examine how students interact and work together. These indicators cover a wide range of things we can measure, like how often students talk to each other and how diverse these interactions are.

One of these indicators tracks their participations in forums. It helps us see how often students take part in online discussions. This indicator also helps us understand what are the topics that more develop the feeling of socialization on the student.

Another indicator is the participation of said forums in time. It looks at when these interactions happen. By counting how often students engage each week, we can see patterns that match up with taught subjects, important dates, and other factors.

There is also an interesting indicator about students' class attendance. This tells us how often students go to their classes. It shows how much they care about learning together in class and being a part of the academic community. However, it is important to note that we could not include this indicator in our research because Iscte uses Fénix to track students class attendance. In this project, the goal is to automatically extract data in real-time. Accessing Fénix in real-time to extract class attendance data was simply not possible, since we are developing a proof of concept.

When we put all these social indicators together, we get a complete picture of how students interact. It helps understand if the student is socially engaged with the learning process, and what might be developing that need to socially engage with their peers.

Table 4.3 –Social Indicators Overview

Name	**Formula**	**Description**
Forum participation by week	The sum of the participation made by a student in a forum per week	The number of times a student participates in a forum/discussion of the UC.
Global Forum Participation	The sum of the participation made by a student in each forum	The number of times a student participates in each forum/discussion of the UC

4.2. Visualization of the Students' Learning Paths

In the upcoming section, we will delve into the visualization of the indicators we discussed earlier. Our primary objective is to present each indicator in a manner that is not only easy to understand but also visually intuitive. To accomplish this, we will be utilizing a combination of charts and tables that aim to provide a clear and insightful representation of each student's learning path.

This visualization strategy is crucial in translating raw data into meaningful insights that can be readily understood by users. By adopting this approach, we seek to enhance the accessibility and usability of the platform, enabling students to effectively interpret the collected data.

Table 4.4 offers a concise summary of all the indicators we are working with. In addition to outlining the nature of each indicator, the table provides insight into the specific visualization approach we have chosen. This preview gives you a glimpse of how we are striving to make the learning journey of each student more comprehensible and engaging through effective data representation.

Table 4.4 – Learning Indicators Visualization Strategy Overview

Indicator Name	**Visualization Strategy**
Content Accessed by Week	Line Chart
Content Accessed by Type	Radar Chart
Assignment Delivery Delay	Bar Chart
Best Quiz Grade	Table
Learning Speed	Table
Consolidation	Table
Learning Progression	Bar Chart
Forum participation by week	Line Chart
Global Forum Participation	Table

CHAPTER
5. Development

This chapter describes how the platform came to life during the development process. The chapter starts by discussing the technological framework that formed the backbone of the platform's creation. Then, it delves into the design phase where we crafted mock-ups to shape the platform's appearance and functionalities. Finally, it explores the practical steps we took to turn these designs into a fully functional platform.

First, we began with the creation of detailed mock-ups that outlined how the platform would look and operate. These mock-ups offered us a visual map of user interactions, navigation paths, and the layout of different elements. They served as a reference, ensuring that the final product would match our envisioned user experience.

Once armed with these mock-ups, we proceeded to the development phase. Using modern technologies and coding practices, we translated these designs into a functioning platform. Our focus was on designing for users, aiming to make the platform intuitive and user-friendly. Our goal was to provide a seamless experience for users as they engaged with the platform's features.

This chapter also showcases the technical tools and frameworks that supported our development journey, providing insights into the coding languages employed and the reasoning behind the technological decisions that were made.

5.1. Technological Environment

The technological environment of the platform showcased in Figure 5.1 supports all the requirements established during this dissertation development.

For the frontend development, we opted for JavaScript, specifically utilizing the React[1]framework. This frontend component interfaces with two separate backend instances. The first backend in Java, utilizing Spring Boot[2], establishes a connection with the Moodle Database. The second backend, implemented in Node.js[3], interfaces with Iscte's services and integrates with Okta[4] to ensure a secure login system utilizing Iscte's credentials.

[1] https://react.dev/
[2] https://spring.io/projects/spring-boot/
[3] https://nodejs.org/
[4] https://www.okta.com/

It is worth noting that this platform does not necessitate the creation of a dedicated database. Instead, it operates in real-time by extracting and presenting processed data directly from Moodle's database. Additionally, all interactions between different components of the platform adhere to the standard REST protocol, ensuring seamless communication and interoperability.

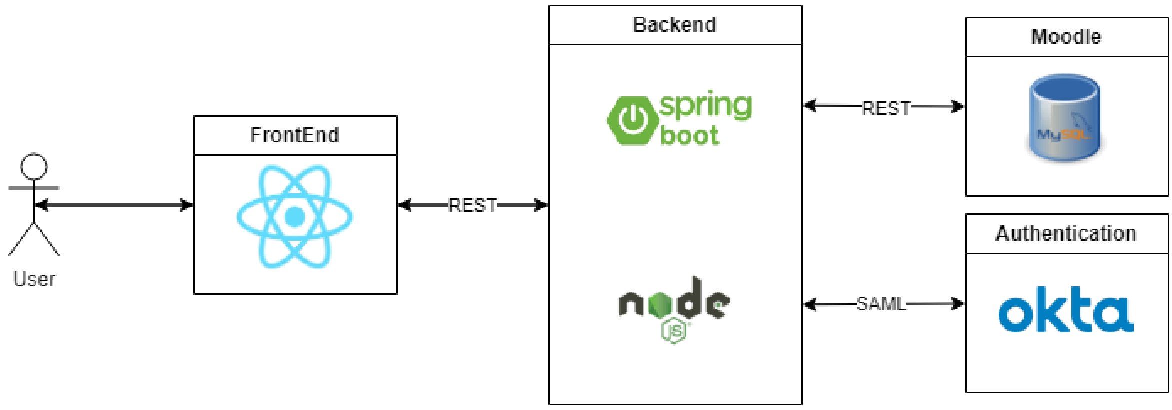


Figure 5.1 – Platform's Technological Environment

In terms of developing the front-end, we opted to create the user interface using the React framework. This decision was based on several strong reasons that highlight the advantages of using React in our development journey. React is well-known for its ability to design dynamic and responsive user interfaces. Its structure, built on a component-based foundation, makes it easier to put together various user interface elements in a modular way, which in turn boosts the reusability and maintainability of code. This approach speeds up the development process and simplifies the task of making changes or adding new features.

Moreover, React's utilization of a Virtual DOM (Document Object Model) system keeps an ideal user interface saved in memory, enhancing rendering efficiency by updating only the essential components (Virtual DOM and Internals, 2023). This strategy minimizes performance limitations and contributes to the platform's overall responsiveness. This aspect gains even more importance as the platform grows, expands its scope, and serves a larger user community.

The backend component is where the crucial logical operations unfold to provide the frontend with the essential data required for shaping the platform's visual aspects. This architecture employs two distinct backends, each catering to specific functionalities.

The first backend, developed using the Spring Boot framework, establishes a direct link with Moodle's database. It takes the form of a REST API, delivering a range of REST services. This strategic design allows the frontend to exclusively concentrate on presenting data, while the backend assumes responsibility for data extraction and preparation. This clear division of labor sets the stage for future scalability and enhancement of the platform's capabilities.

The second backend plays a pivotal intermediary role in facilitating Iscte's Okta login system. This mechanism ensures that each student can exclusively access their individualized information. To achieve this, students utilize their Iscte credentials for login, initiating communication with Iscte's Okta through the Node.js-based backend. The application of the Security Assertion Markup Language (SAML) protocol serves as the channel for secure interactions between the two systems. Notably, Iscte's well-secured login system extends across various student platforms, including Moodle and Fenix, the university's designated learning management tools.

Moreover, it is worth noting that despite Moodle offering its own API for extracting data through the web services app, using it comes with certain challenges. One key limitation is that the API doesn't allow us to extract logs, which is an important aspect for our platform. Another challenge is that relying solely on the API for data extraction could potentially strain the database due to the high number of operations it would require, as the operations the API enables are not optimized for the data we need to extract. Given our commitment to not impact Moodle's database performance, we had to find an alternative approach.

To address these issues, we decided to create Stored Procedures in the SQL database. This approach comes with several advantages. First, it allows database administrators to control who can access and use these procedures, ensuring data security. Second, it enables Iscte to be selective about the information we extract. Unlike the API, which provides all available data in each function, Stored Procedures allow us to extract only the specific data we need. This flexibility is particularly important when dealing with sensitive information that should remain protected.

The technology stack we used for this project relies on open-source frameworks. We chose React, an open-source JavaScript library, for the frontend development. For the backend, we utilized two open-source technologies: Spring Boot and Node.js. These were chosen to serve different functions of the platform. Additionally, most of the components we integrated into the project were sourced from the NPM (Node Package Manager), a tool that simplifies the process of adding community-developed components to our code.

In addition, Table 5.1 provides a summarized overview of the key tools that played a crucial role in the development process of this dissertation project.

Table 5.1 – Technological Stack used In the Thesis

Tool	Description	Purpose
Visual Studio Code	IDE of choice	Develop both the frontend (React) and the backend (NodeJS and Spring-Boot)
MySQL workbench	Platform to work on the database	Study Moodle's architecture and develop the Stored Procedures
Insomnia	Platform to test endpoints	Test backend endpoints

5.2. Requirements definition

As we delved into the platform development process, it was crucial to outline a clear list of requirements. These requirements serve as the guiding principles that shape our approach, covering everything from the technical intricacies of the platform to the broader objective of enhancing insights into learning paths.

Table 5.2 provides a visual representation of the functionalities that we have carefully planned for this thesis.

Table 5.2 – List of Features of the Platform

Requirement	State
LogIn – Through Iscte's authentication platform (okta)	Done
Visualization of Learning Indicators – Engagement Indicators	Done
Visualization of Learning Indicators – Cognitive Indicators	Done
Visualization of Learning Indicators – Social Indicators	Done
Visualization of Last Moodle Access Data	Done
Comparison Between Student' and Class indicators	Done
Showcase of Student's UCs	Done
Showcase of Moodle's username	Done
Ability to change the UCs learning path indicators	Done
On Hover effect to showcase the exact values of each chart	Done

5.3. Mock-ups

Within this sub-chapter, we delve into a display of mock-ups that were crafted to support the development of the platform. These mock-up designs act as a window that offers an idea into the user experience we envision, presenting a tangible preview of the platform's layout, functionalities, and overall visual appeal.

The creation of these mock-ups holds a pivotal role in delineating project functionalities and requisites. Serving as visual aid for the platforms’ appearance and features, providing a practical comprehension of the necessary components and interface dynamics. It closes the gap between the abstract thought of what the platform should be, and the design of how will be. This crucial process not only aids in the early-stage identification of potential gaps or incongruities in proposed functionalities but also supports iterative refinement. Consequently, this contributes to precise requirement definition, curbing the risk of misunderstandings and elevating the overall quality of the ultimate product.

It is important to note that the idea beyond this platform is simplicity and accessibility, so the objective is to develop a minimalistic, simple, and user-friendly platform.

Figure 5.2 grants a glimpse into the app's login page, serving as the redirection of students to Okta services for login using Iscte's credentials. As the page is only a redirection to OKTA services, it has no depth on it, it is a button that redirects the user. Meanwhile, Figure 5-3 portrays the landing page post-login, spotlighting the comprehensive dashboard that charts students' learning pathways across various UCs. The inclusion of a select box in the top left corner facilitates user interaction by enabling students to navigate between different UCs to access their respective learning paths.

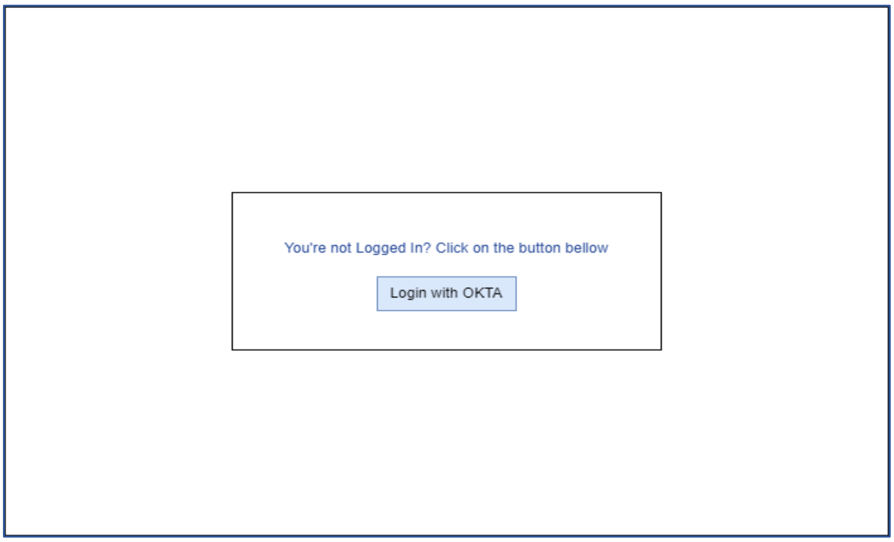
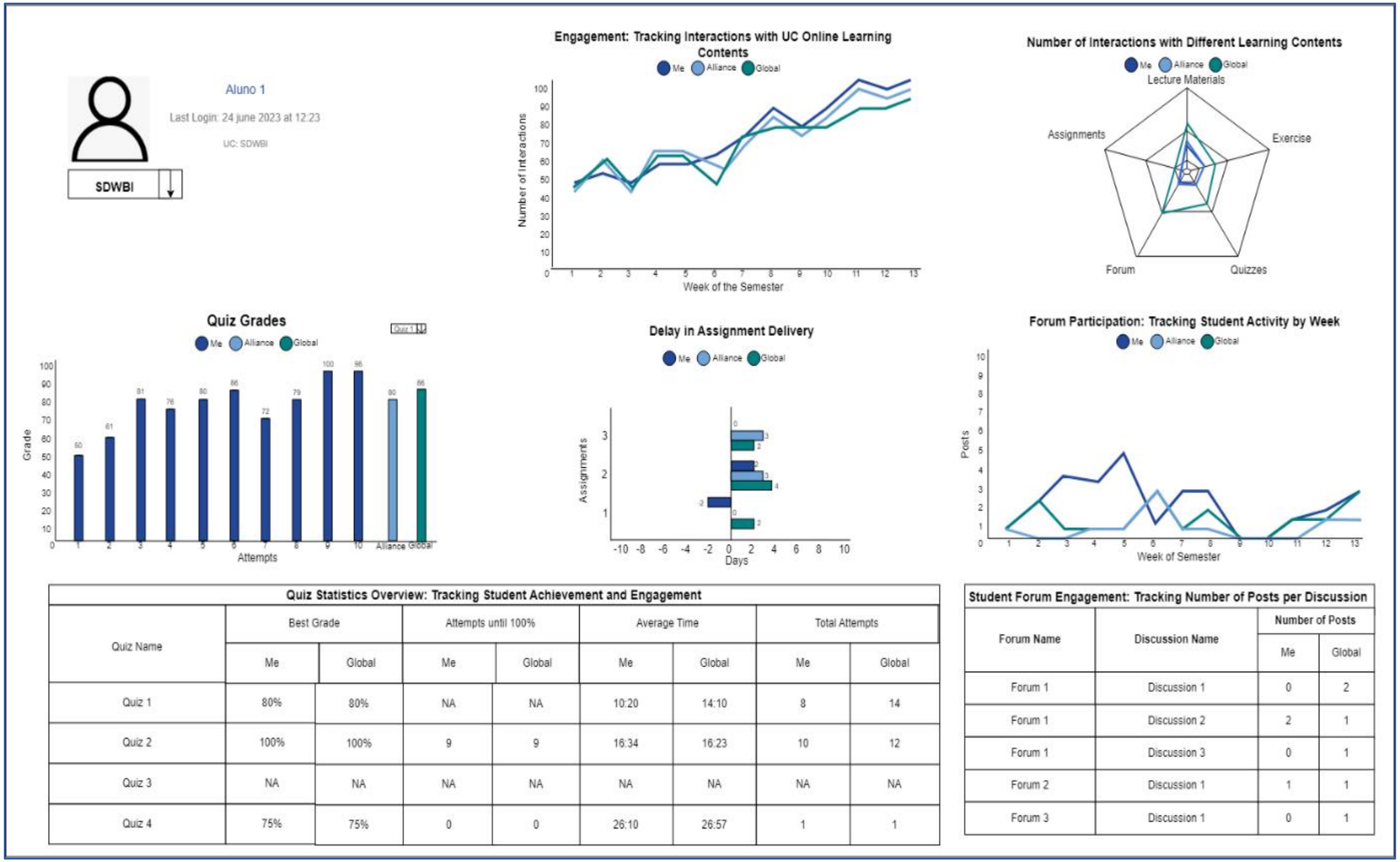


Figure 5.2 – Log-In Page Mock-up



Quiz Statistics Overview: Tracking Student Achievement and Engagement								
Quiz Name	Best Grade		Attempts until 100%		Average Time		Total Attempts	
	Me	Global	Me	Global	Me	Global	Me	Global
Quiz 1	80%	80%	NA	NA	10:20	14:10	8	14
Quiz 2	100%	100%	9	9	16:34	16:23	10	12
Quiz 3	NA	NA	NA	NA	NA	NA	NA	NA
Quiz 4	75%	75%	0	0	26:10	26:57	1	1

Student Forum Engagement: Tracking Number of Posts per Discussion			
Forum Name	Discussion Name	Number of Posts	
		Me	Global
Forum 1	Discussion 1	0	2
Forum 1	Discussion 2	2	1
Forum 1	Discussion 3	0	1
Forum 2	Discussion 1	1	1
Forum 3	Discussion 1	0	1

Figure 5.3 – Dashboards Page Mock-up

5.4. Development and Integration with Moodle

The integration of the platform with Moodle commences by establishing a connection between the application and Moodle's database. This linkage was established using Moodle's API Web App Services in combination with the development of stored procedures.

Figure 5.4 illustrates a practical instance of how the API facilitates information retrieval utilizing JSON (JavaScript Object Notation), while Figure 5.5 exemplifies a stored procedure in action during the data extraction process.


```json
{
  "id": 2,
  "shortname": "UC",
  "categoryid": 1,
  "categorysortorder": 10001,
  "fullname": "Unidade Curricular 1",
  "displayname": "Unidade Curricular 1",
  "idnumber": "",
  "summary": "",
  "summaryformat": 1,
  "format": "topics",
  "showgrades": 1,
  "newsitems": 5,
  "startdate": 1679612400,
  "enddate": 1711148400,
  "numsections": 4,
  "maxbytes": 0,
  "showreports": 0,
  "visible": 1,
  "hiddensections": 1,
  "groupmode": 0,
  "groupmodeforce": 0,
  "defaultgroupingid": 0,
  "timecreated": 1679604474,
  "timemodified": 1679604474,
  "enablecompletion": 1,
  "completionnotify": 0,
  "lang": "",
  "forcetheme": "",
  "courseformatoptions": [
    {
      "name": "hiddensections",
      "value": 1
    },
    {
      "name": "coursedisplay",
      "value": 0
    }
  ],
  "showactivitydates": true,
  "showcompletionconditions": true
}
```


Figure 5.4 – Example of a JSON Data Structure

```
call moodle_db.Posts_date_UC(2);
```

	PostTime	UserID
▶	2023:03:23:08:03:38	2
	2023:03:23:08:03:46	2
	2023:03:23:10:03:31	3
	2023:03:23:10:03:13	3
	2023:04:04:04:04:45	5

Figure 5.5 – Example of Stored Procedure call and the Reply

The initial phase encompassed identifying the necessary information and locating its storage within Moodle. For the most part, Moodle automatically archives this information, except for tags. To activate the tagging feature, course teachers must manually associate tags with specific learning resources. This integration is crucial for smooth interaction with our application.

Enabling tags is a straightforward process. Teachers select a particular course and enter "Edit Mode." They then pinpoint the learning content requiring tagging, proceed to modify its settings, and access the "Tags" dropdown menu. Here, teachers select the relevant tag and confirm the changes. Notably, the platform employs tags such as "Lecture Materials," "Exercises," "Assignment," "Forum," and "Quizzes." These tags play a significant role in the learning indicator, which identifies the nature of the content students engage with. It is important to emphasize that these tags are applicable solely to learning content categorized as "File." Other types of learning content, like quizzes or assignment submissions, possess inherent characteristics that obviate the need for specific tags.

Visual representations in Figures 5.6, 5.7, and 5.8 illustrate this sequential process, demonstrating how to transition into "Edit Mode," modify learning content settings, and apply tags. These visuals are based on the standardized Moodle installation, acknowledging that varying Moodle platforms may present distinct configurations and aesthetics due to customizable plug-ins and individual site preferences.

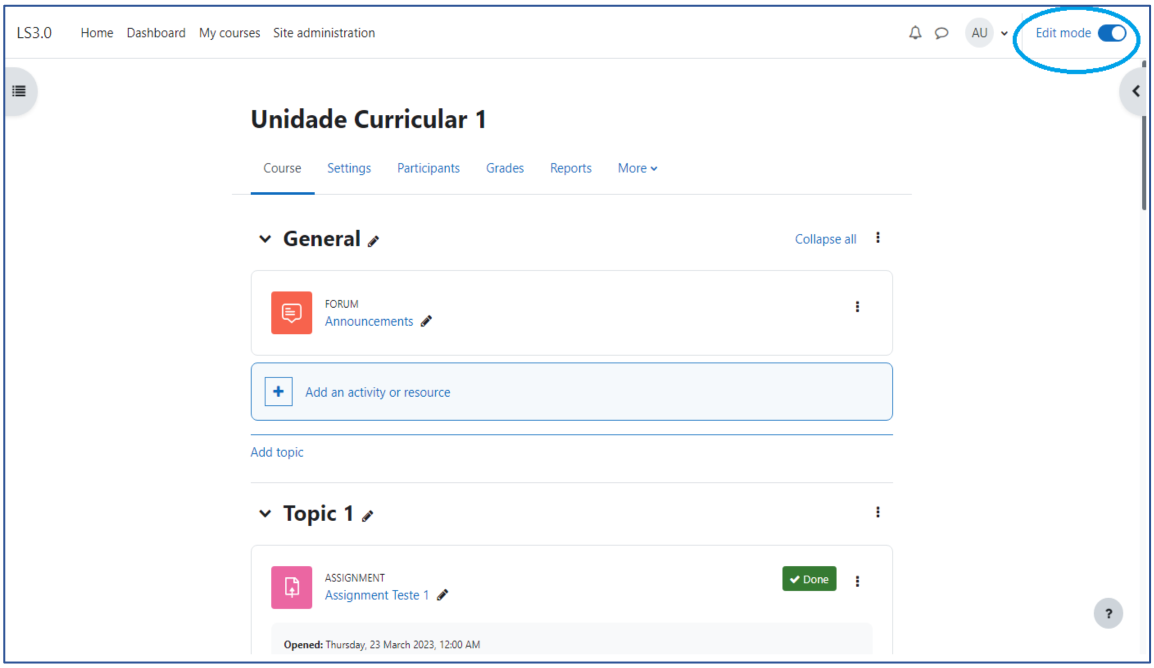


Figure 5.6 – Demonstration of the Tag System (Edit Mode)

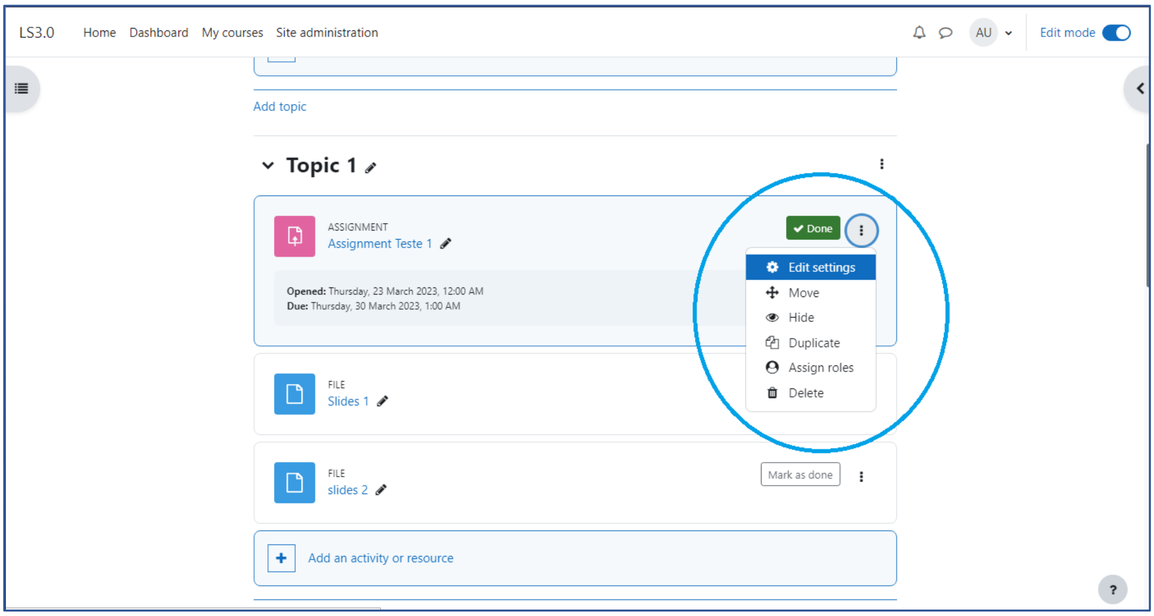


Figure 5.7 – Demonstration of the Tag System (Edit Settings)

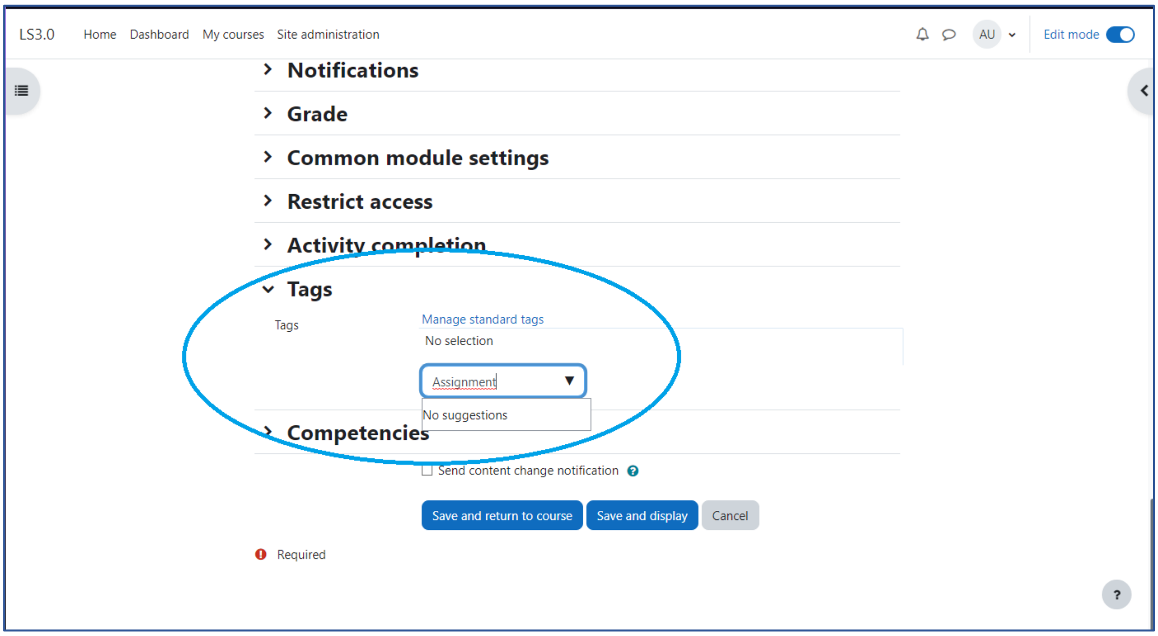


Figure 5.8 – Demonstration of the Tag System (Add Tag)

Subsequently, the focus shifted towards the development of the Stored Procedures. The primary objective behind crafting these Stored Procedures was to meticulously extract pertinent information from the database while minimizing the database query load. A total of 22 distinct Stored Procedures were meticulously formulated and integrated into the system.

It is important to emphasize that Stored Procedures operate outside the domain of Moodle's inherent structure. Consequently, they must be integrated into the database itself to function. This step assumes a pivotal role in the platform's implementation as, without this installation, the platform will not work.

Figure 5.9 presents a tangible illustration of the Stored Procedure concept. This figure serves as an exemplar, depicting how the stored procedures were built.

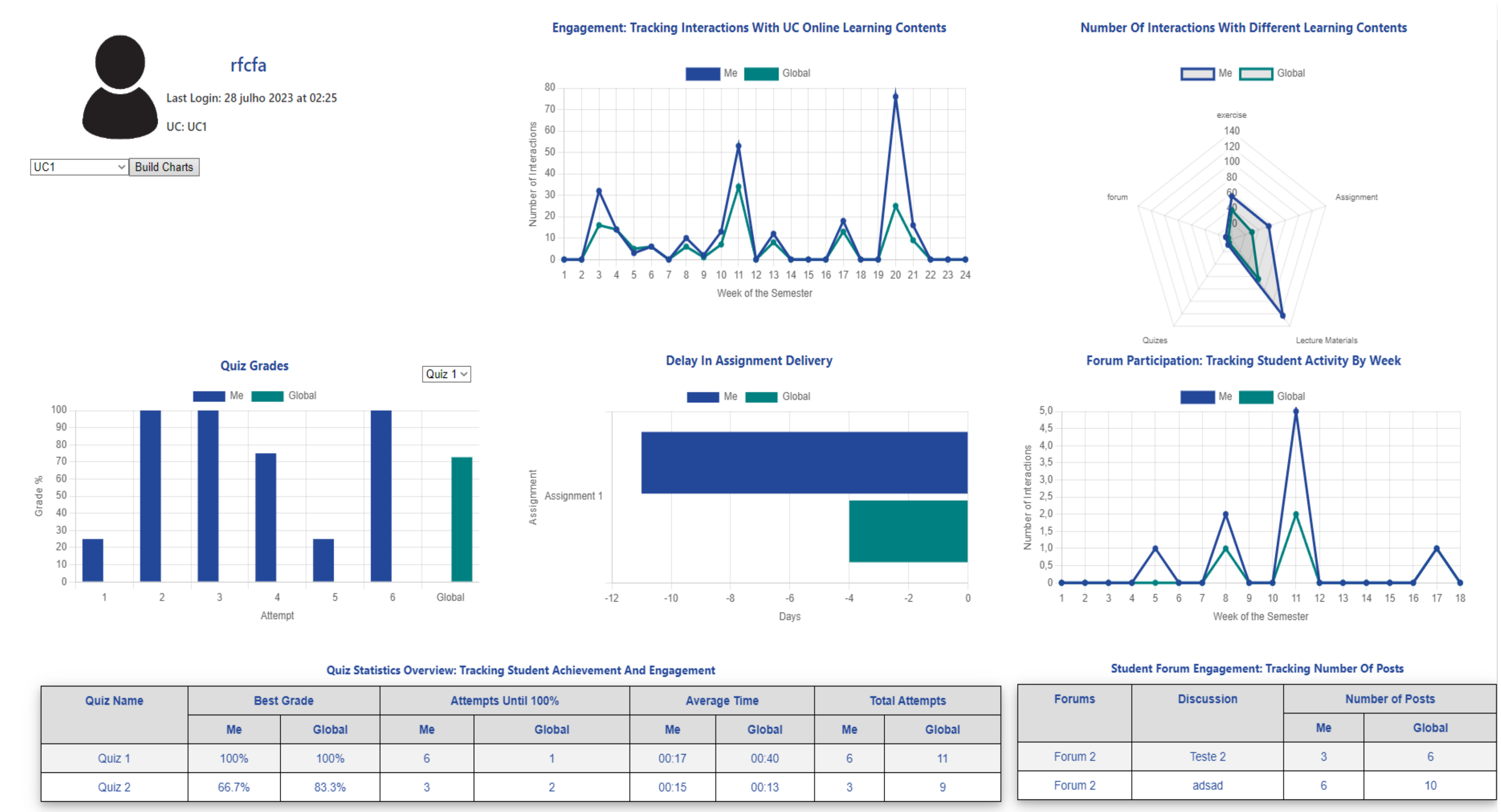
```
PROCEDURE `Posts_date_UC`( IN CourseID INT)
BEGIN
        SELECT DATE_FORMAT(FROM_UNIXTIME(fp.created), '%Y:%m:%d:%h:%m:%s')
        AS PostTime, fp.userid as UserID
        FROM mdl_forum_posts fp
        JOIN mdl_forum_discussions d ON fp.discussion = d.id
        JOIN mdl_forum f ON d.forum = f.id
        JOIN mdl_user u ON fp.userid = u.id
        JOIN mdl_course c ON d.course = c.id
        where f.course=CourseID;
END
```

Figure 5.9 – Example of a Stored Procedure

While the Stored Procedures successfully provided access to the data, it is important to acknowledge that not all the data was immediately ready for use. Refinement was required for a significant portion of the data extracted, a common scenario in most applications. The Spring Boot instance served as the intermediary, bridging the gap between the raw database data and the frontend's presentation needs. This connection was established through REST API, ensuring the seamless delivery of processed and relevant information to the frontend.

Subsequently, attention turned to the development of the frontend. Using React, the frontend was constructed in alignment with the predefined mock-ups. The data sourced from Moodle assumes a central role, serving as the foundation for generating charts and populating tables. This data-driven approach culminated in the creation of a dynamic dashboard that effectively visualizes each student's learning trajectory.

A visual representation of the completed dashboard page, as envisioned in the mock-ups, is illustrated in Figure 5.10. This succinctly captures the integration of design and data, resulting in a functional and visually coherent user interface.



Quiz Name	Best Grade		Attempts Until 100%		Average Time		Total Attempts	
	Me	Global	Me	Global	Me	Global	Me	Global
Quiz 1	100%	100%	6	1	00:17	00:40	6	11
Quiz 2	66.7%	83.3%	3	2	00:15	00:13	3	9

Forums	Discussion	Number of Posts	
		Me	Global
Forum 2	Teste 2	3	6
Forum 2	adsad	6	10

Figure 5.10 – Platform's Dashboard Page

Each student is granted access to their individualized learning path within each enrolled UC, ensuring their privacy and data confidentiality. It is important to highlight that the specific learning paths of other students remain inaccessible. Instead, students can view their learning path metrics for the UC, safeguarding sensitive and personal information. To accomplish this, integration with Iscte's login system was established. Iscte employs Okta for user authentication, and this was seamlessly incorporated into our platform using a NodeJS Server and SAML protocol. Upon reaching the login page, students are directed to Iscte's Okta for authentication and then seamlessly redirected to their personalized dashboard upon successful authentication. If a student is already logged into Moodle prior to accessing our platform, they are instantly directed to their dashboard, eliminating the need to log in again. This also enabled the creation of a global link, where if the student navigates to the link, it automatically redirects the student to the platforms if they are authenticated and, if not, it redirects them to Iscte’s authentication system. It is worth noting that Iscte's authentication system boasts two-factor authentication, which further bolsters our platform's security measures.

Figure 5.11 depicts the login page's visual representation, adheres to the mock-up design. Upon clicking the login button, users are seamlessly directed to Okta's interface, an example of the Okta’s authentication system is showcased in Figure 5.12, 5.13, and 5.14. This integrative approach ensures both user convenience and stringent security.

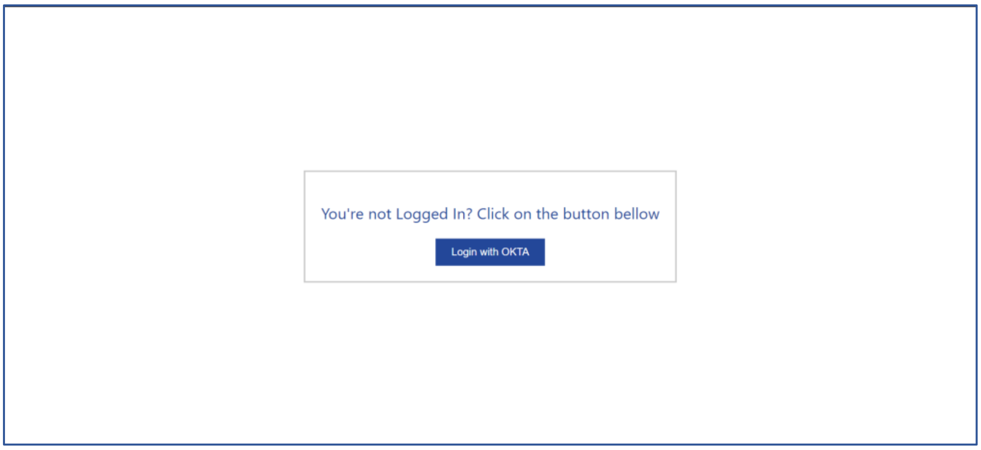


Figure 5.11 – Platform’s LogIn Page

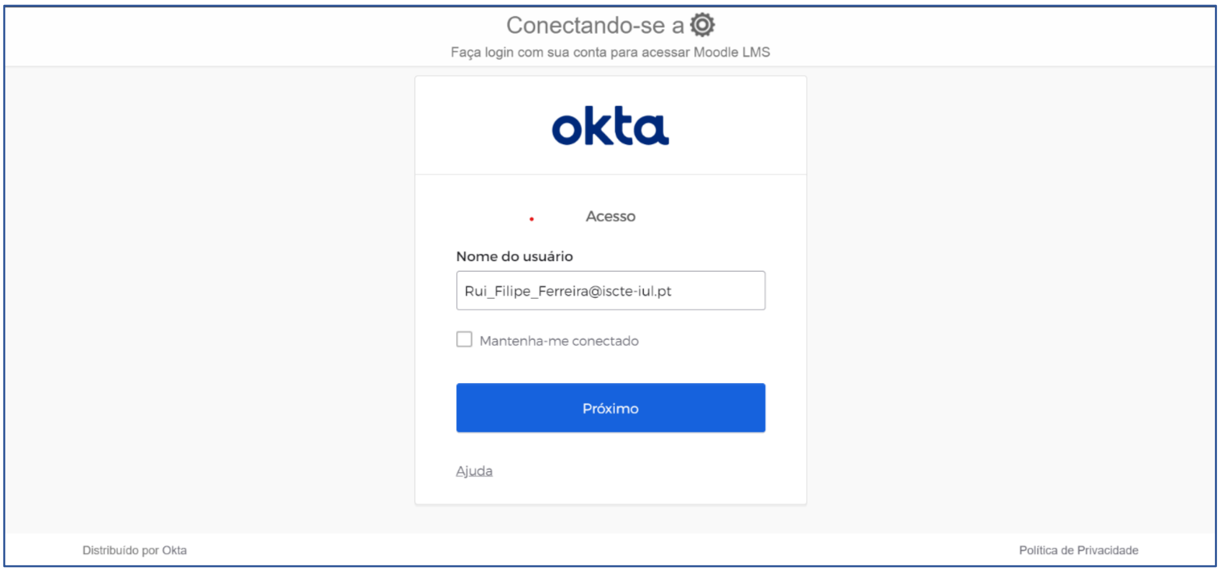


Figure 5.12 – Example of a LogIn Through Iscte's OKTA (Username)

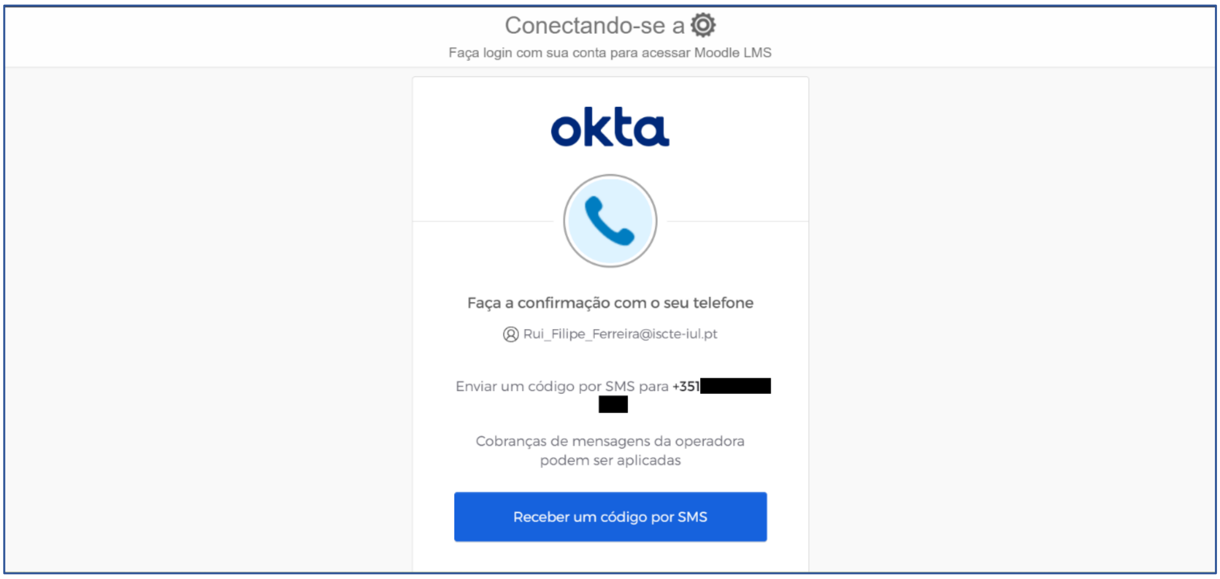


Figure 5.13 – Example of a LogIn Through Iscte's OKTA (Phone Verification)

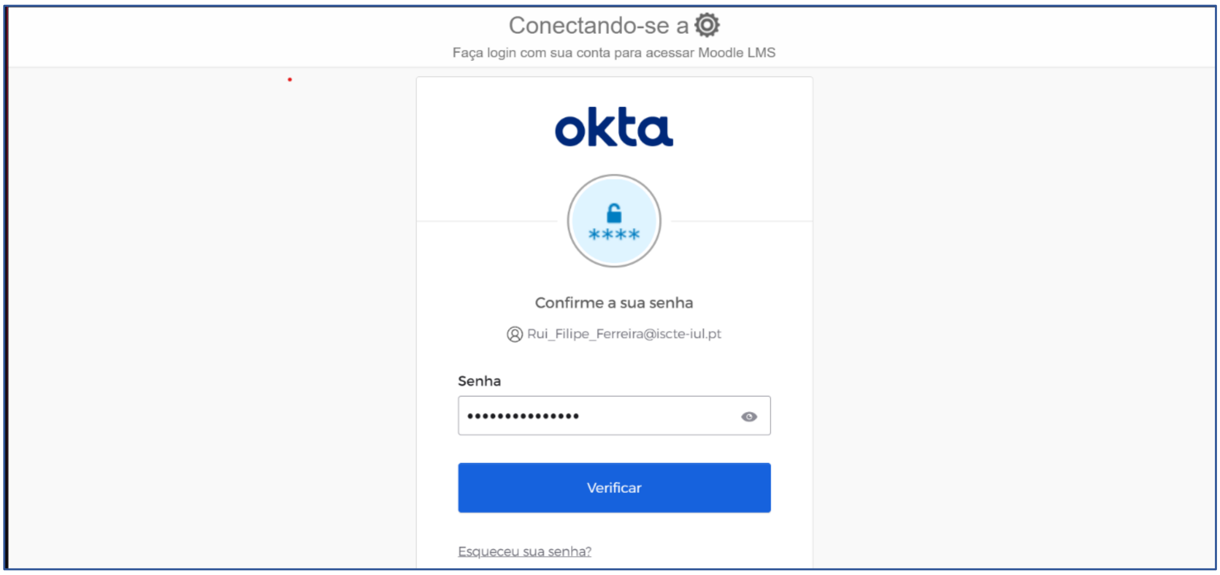


Figure 5.14 – Example of a LogIn Through Iscte's OKTA (Password)

CHAPTER 6

6. Validation

This chapter presents the validation process for the platform developed in this thesis. Validation was conducted through a questionnaire designed to gather insights on how students perceive the platform. Participants were given an opportunity to explore the platform and share their opinions.

A total of 24 students participated in the questionnaire, which was administered using Google Forms. The questionnaire was structured into three sections aimed at achieving different objectives: characterization of the participants, familiarity with LMSs, and validation of the platform and its features (see Appendix A).

The first section of the questionnaire focused on participant demographics, including age and academic status. It is worth noting that the participants came from diverse universities and courses. In the second section, participants were asked about their experience with LMSs and their preferences regarding platforms that track their interactions on these systems. Finally, the third section centered on the validation of the platform itself. Participants were queried about their willingness to use a platform like the one presented, their favorite features, and whether they believed such a platform would enhance their learning experience.

6.1. Participants Characterization

Figure 6.1 showcases the age of the participants, where it is shown that most of the participants belong to the age group of 23 to 25 years (54.2%), followed by the ages between 20 to 22 years (20.8%). The rest of the participants are equally divided between the two age groups of 17 to 19 years and more than 26 years, corresponding to 12.5% each.

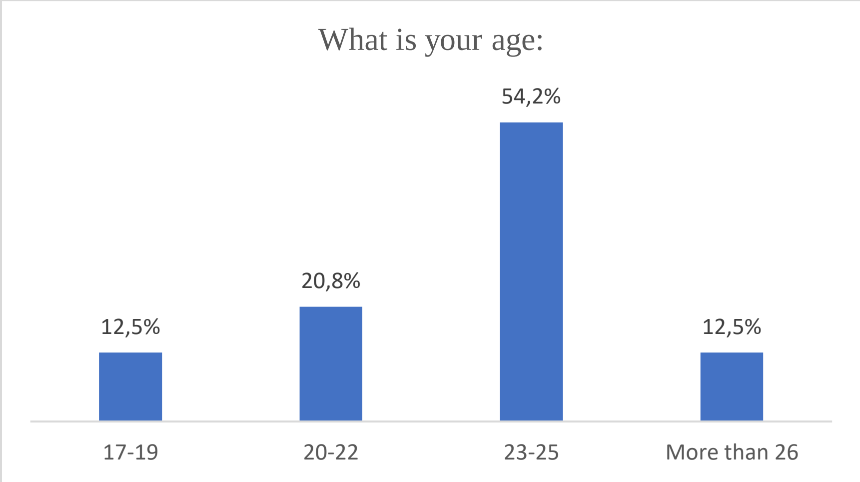


Figure 6.1 – Participants Age (n=24)

In total, 75% of the total participants are graduate students during the academic year of 2022/2023 and 25% are undergraduate students, no participant was a doctoral student.

Both the ages and the academic statuses lead us to believe that most of the participants had experienced using LMS platforms, which is an asset for the aim of this questionnaire.

Also, the participants belong to different universities, not all participants belong to Iscte, which helps us understand how most of the students would see the platform, and not just people that study at Iscte.

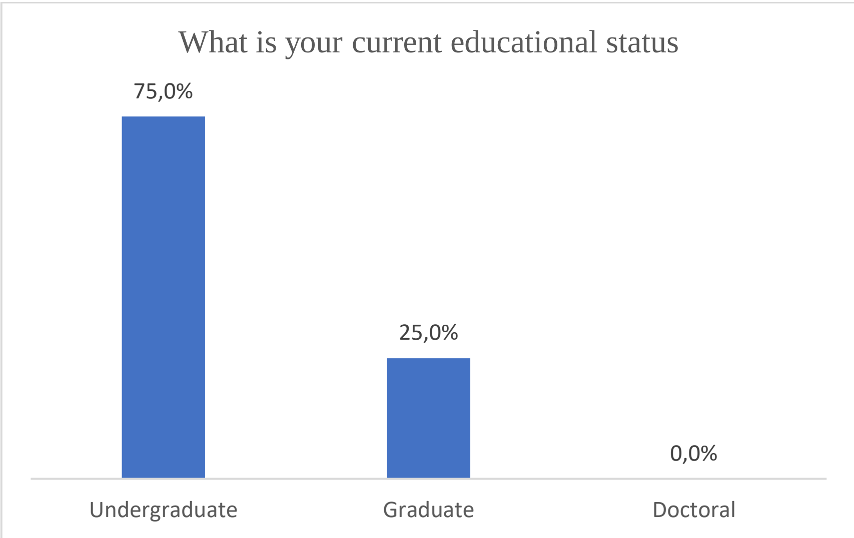


Figure 6.2 – Participants Educational Status (n=24)

6.2. LMS Familiarity

Corresponding to the use of LMS platforms, it was identified that most of the participants are familiar with it (58.3%), the ones that are very familiar with it are 20.8% of the total participants, while 16.7% are only somewhat familiar with LMSs. 4.2% are not familiar with LMS platforms

(Figure 6.3). Figure 6.4 showcases the frequency in which they use a LMS platform. 50% use it several times a week, 20.8% use it only once a week, 16.7% use it rarely and 12.5% use it daily.

This shows that most of the participants are either very familiar or familiar with their use, which is important for the validation as the perception of LMS features and use is important to use the platform created during this thesis.

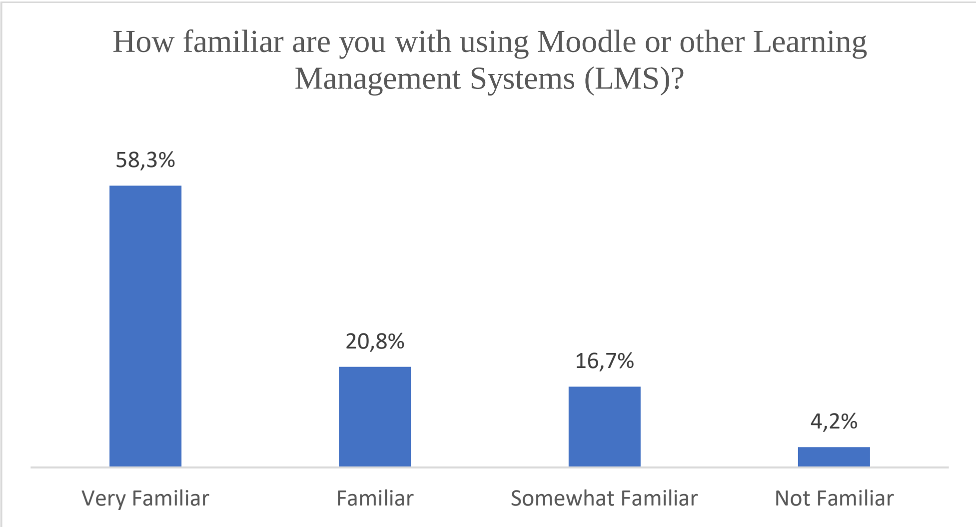


Figure 6.3 – Familiarity using LMS (n=24)

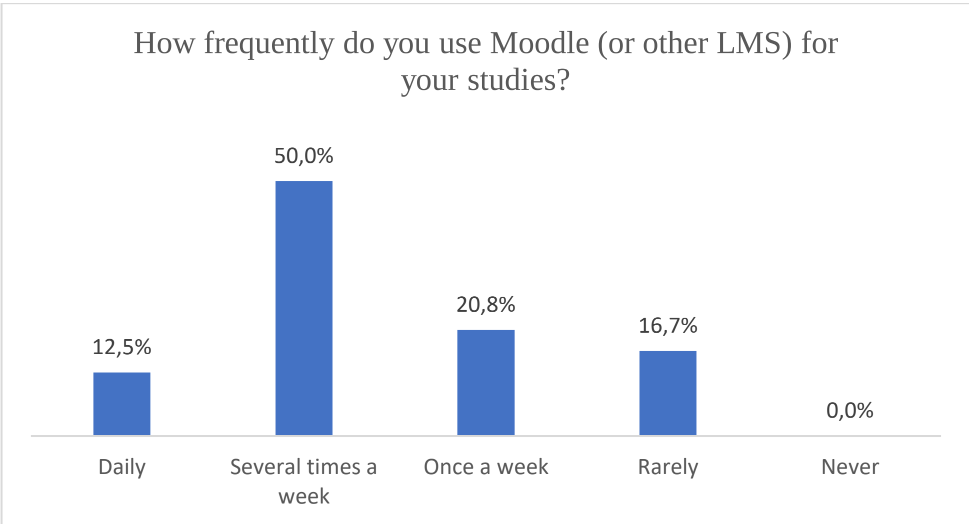


Figure 6.4 – Frequency of using LMS (n=24)

When asked about the participants' perception of how useful it would be to have access to detailed insights about their learning activities, most of them had a neutral opinion (45.8%), followed by 37.5% thinking it would be useful and 12.5% thinking it would be very useful.

Only 4.2% thought it would be not useful. These answers showed that either the participants are neutral to its use or think it would help them.

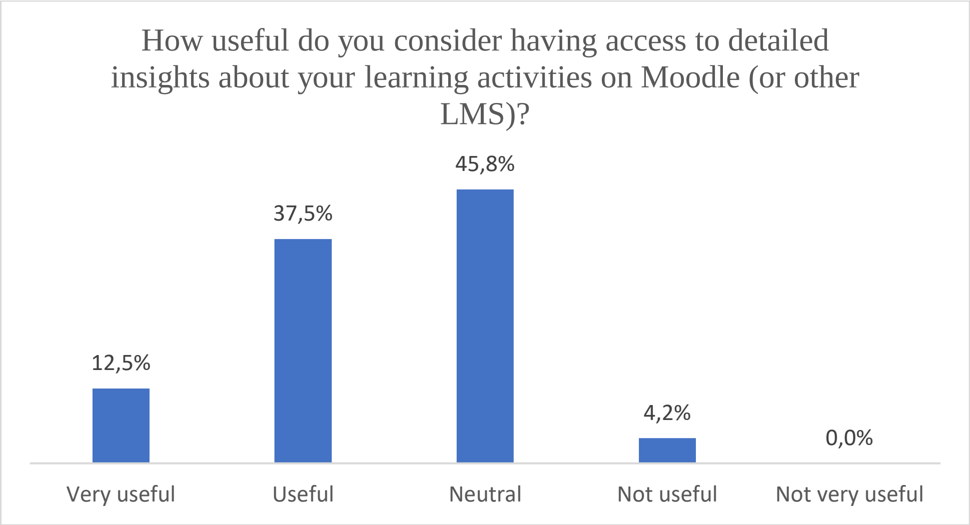


Figure 6.5 – Usefulness of tracking learning activities (n=24)

Relatively to the possible use of a platform that enables you to visualize your learning path, most of the participants either answered neutral or that they were likely to use it (33.3% each), followed by 25% that say they would be very likely to use it and 8.3% think it would be unlikely for them to use that kind of platform. It shows that overall, the participants would use a platform with those features.

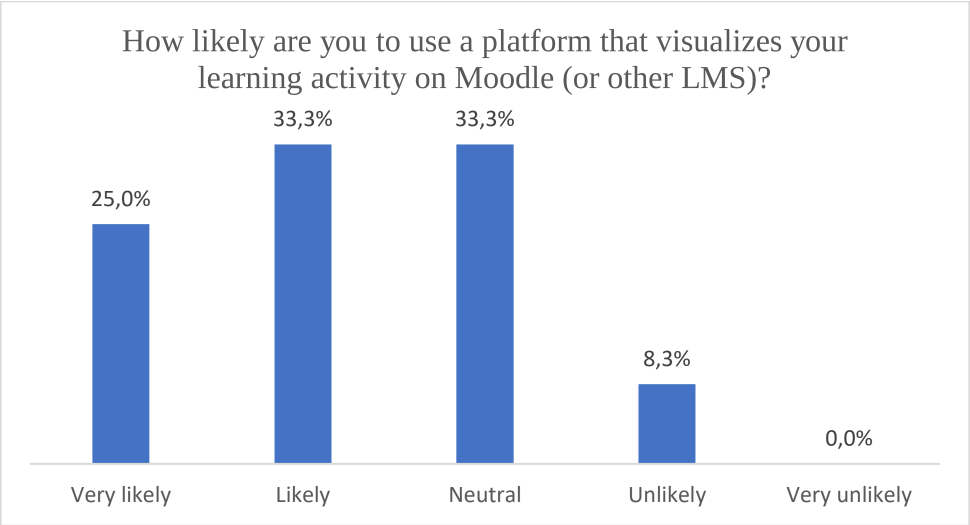


Figure 6.6 – Likeliness of using a platform that tracks learning activity on LMS (n=24)

6.3. Platform Validation

At this section of the questionnaire, we first identify how the platform is perceived by the participants. They identified the tracking of interactions, the history of grades on the quizzes, their stats, and the interactions divided into types of learning contents the most valuable features on the platform, having 83.3%, 79.2%, 79.2%, and 58.3% of the participants, respectively, thinking is a valuable feature. On the other hand, the stats of forums, the participation on them and the delay in the delivery of assignments only has 25%, 33.3% and 29.2% of the participants respectively. Looking at the feature to compare the students' learning path with their class, 37.5% thought it was neutral, while 29.2% and 20.8% thought it was useful and very useful respectively. Still some participants thought it was not very useful (12.5%). Both answers give us insight into what are the most important features and what the participants find most interesting in the platform.

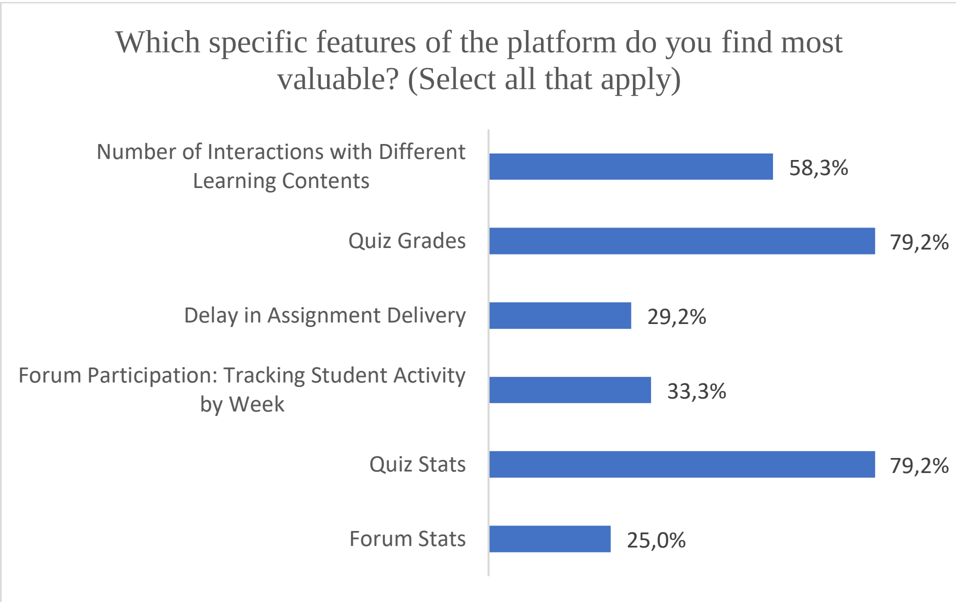


Figure 6.7 – Most Valuable Features on the platform (n=93). This question enabled multiple answers from participants.

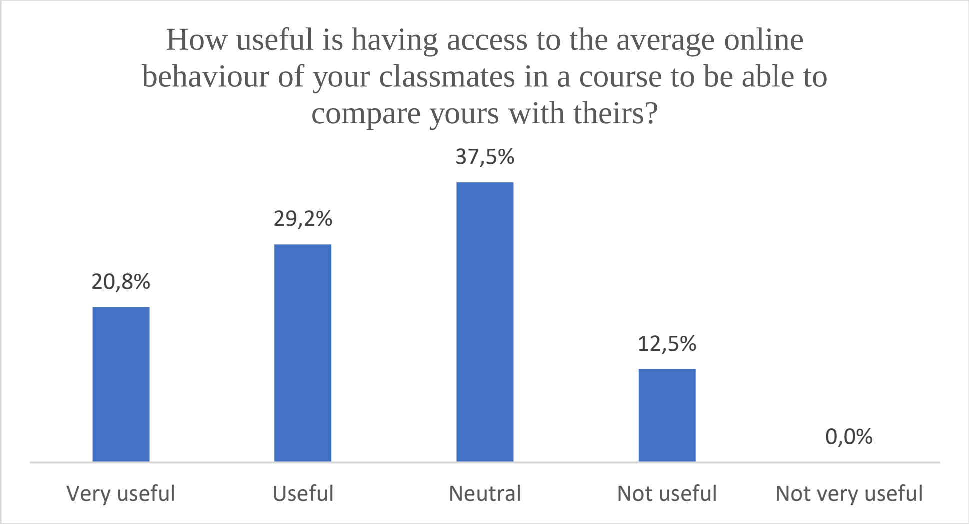


Figure 6.8 – Usefulness of comparing the learning behavior with the class (n=24)

Figure 6.9 showcases the distribution of how intuitive the participants find the platform, where most of the participants thought it was either very intuitive or intuitive, having the same percentage of answers of 33.3%. 29.2% thought it was neutral and 4.2% thought the platform was not intuitive. Moreover, at Figure 6.10, most of the users think this platform met their expectations regarding the visualization of learning paths, while 33.3% thought it was neutral, 16.7% thought it exceeded expectations and 8.3 thought it was bellowing their expectations. Analyzing both the questions, it gives us insight into the platform, that even though users overall see it as intuitive and that it meets their expectations, it still can be improved.

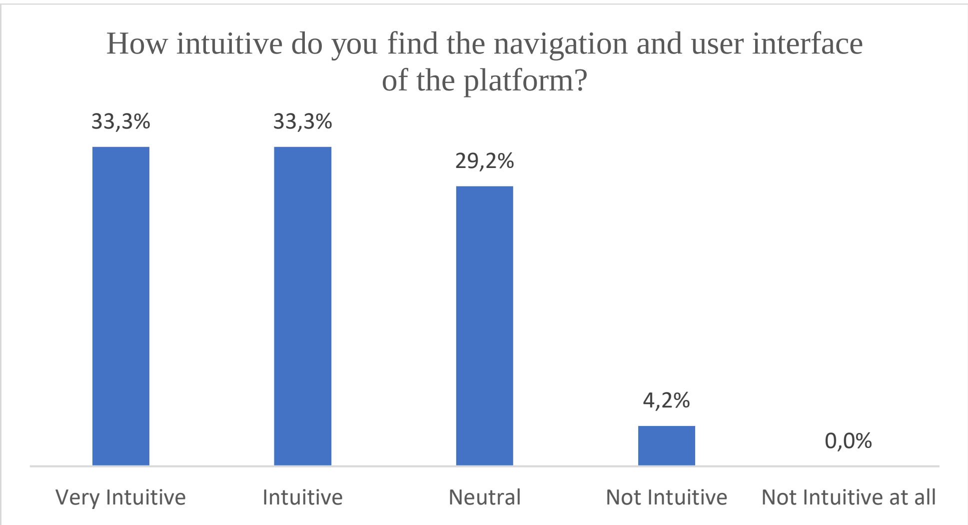


Figure 6.9 – How intuitive is the platform (n=24)

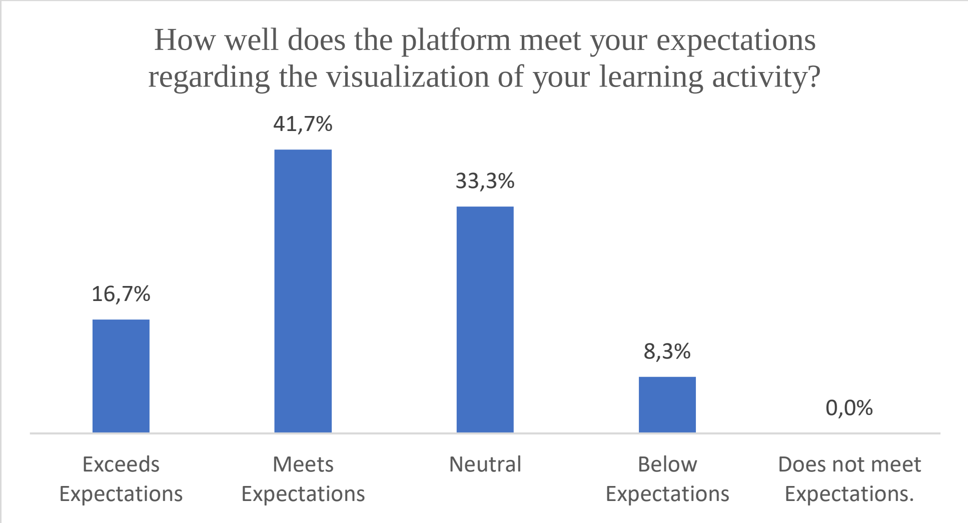


Figure 6.10 – Expectations of the platform (n=24)

When asked if they felt confident in interpreting the data and insights from the platform, 50% of the participants were neutral, 29.2% and 16.7% were confident and very confident respectively, while 4.2% were not very confident (Figure 6.11). Figure 6.12 shows if the participants think this platform would positively impact their academic performance, and most participants (66.7%) answered that they agree it would positively impact their academic performance and 20.8% strongly agree, while 12.5% disagree that it would have a positive impact. Both questions give us insight into the clearness and the impact of the learning path indicators, overall, the answers given reflect that the impact would be positive and it would help the students, even though the neutral answers in the confidence the participants have in interpreting the data and insight to make decisions on their learning strategies also tell us that the way the indicators are shown could be improved.

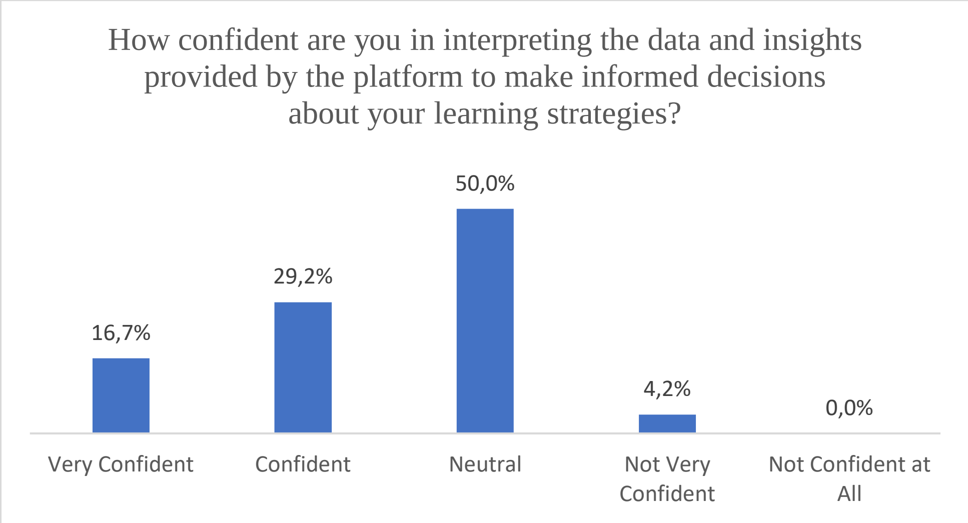


Figure 6.11 – Confidence on interpreting the data provided by the platform (n=24)

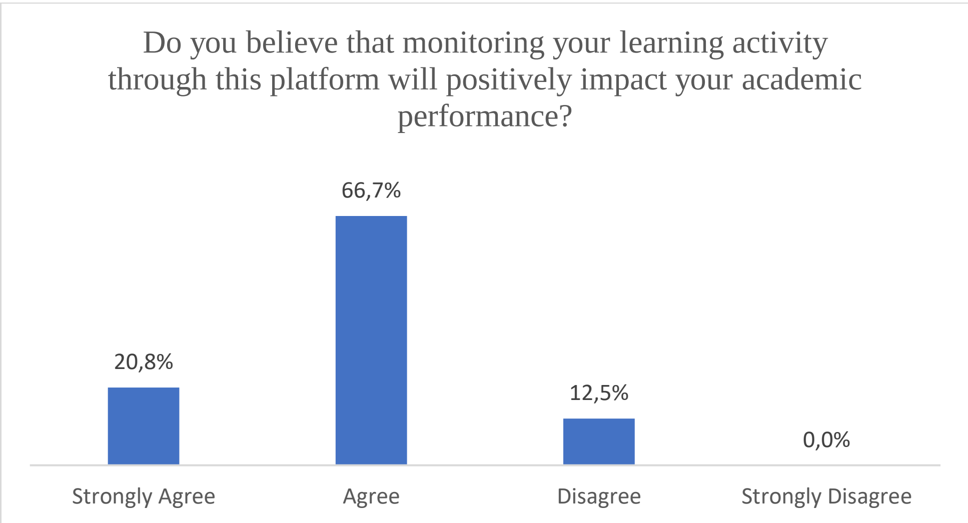


Figure 6.12 – Impact of the platform in the academic performance (n=24)

While analyzing if the participants would use the platform, the most common answers are that they would use it often and occasionally, with 33.3% of the answers in each option, followed by very often and rarely with 16.7% each (Figure 6.13). It shows us that the participants overall would use the platform, but the number of times they would use it is well divided into just occasionally and often.

Finally, when asked about how satisfied they are with the platform's ability to help monitor and improve the learning process, 58.3% said they were satisfied with it, 20.8% said they have a neutral opinion on the platform, 12.5% are very satisfied and 8.3% are dissatisfied. Overall, this gives the platform a good rating, but it shows there is things that could improve, such as how clear the indicators are shown, the interface and maybe some kind of visual aid to help students improve their learning performance with these indicators.

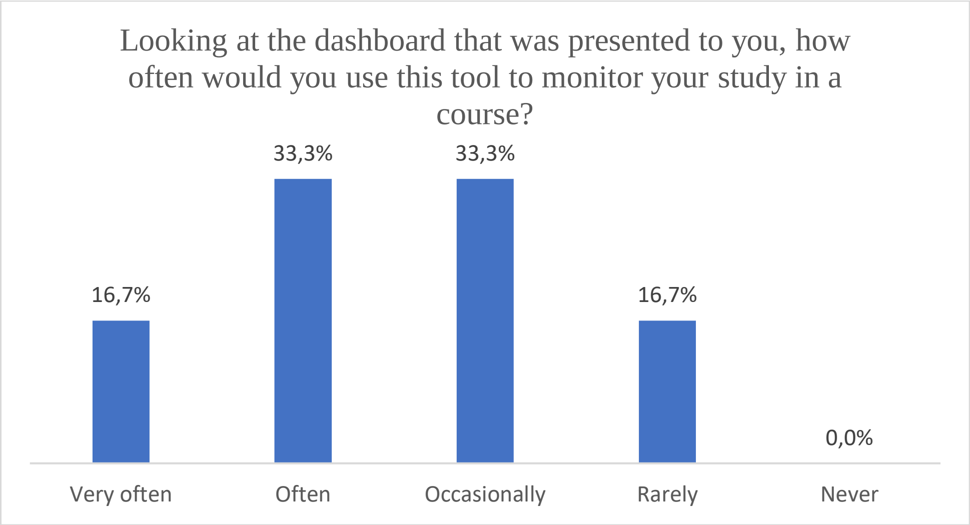


Figure 6.13 – Frequency of using the platform (n=24)

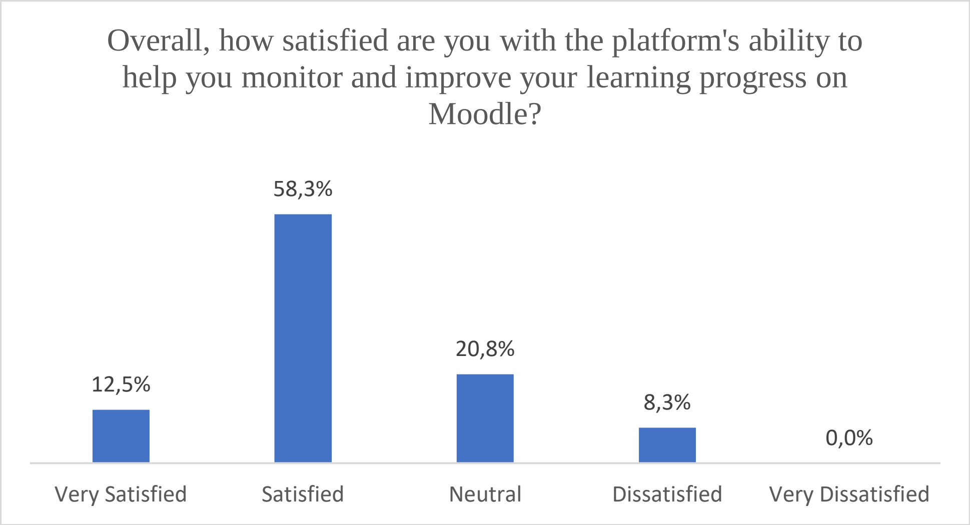


Figure 6.14 – Satisfaction with the platform (n=24)

CHAPTER 7

7. Conclusion

The platform developed to visualize and monitor the students' learning paths aims to make students more engaged, help them organize and plan better their study, and notice what might be the behaviors that result in shortcomings during an UC, making it a better and more interactive learning experience.

The platform developed in this dissertation can be accessed after logging in through Iscte's authentication system where, for instance, if the user is already authenticated on Moodle or other Iscte's platform, the user is automatically logged into his platform. The platform does not have a database, as it uses the data stored in Moodle's database and, as a real-time learning path visualization tool, it needs to access the most recent information every time the dashboard is going to be built. The backend that connects with Moodle's database is an API REST, granting the communication and integration between the different layers of the platform in an easy to understand, use and maintain way.

The learning indicators found in Moodle cover three categories: engagement indicators, cognitive indicators, and social indicators. As the learning process is a complex process, it means that all the indicators interact with themselves, for example, a good social learning experience leads to better engagements and so on. The platform consists of an interactive dashboard with charts, graphs, and tables to better showcase the students' learning paths and enable its monitoring. It also has the feature to choose what UC that the student wants to check his learning path, not all UCs might have the same type of learning process, so it is important to separate them. Moreover, there is the possibility to look at the average behavior of the students that are enrolled in the same UC. This feature adds an aspect of comparison and competition to the platform, where students might not want to fall beyond their peers.

After the development of the platform, its validation was made through a questionnaire, where the participants were asked about their familiarity with LMS and about how the platform developed in this dissertation was perceived. Overall, the platform was well received by the participants, where 87.5% agreed that the platform would improve their academic performance (66.7% agreed and 20.8% strongly agreed), which gives motivation to improve the platform and to develop more features into it. Given that the platform is already integrated with Iscte's Moodle, it is possible to fully deploy this platform into the university's LMS.

7.1. Research Questions

In this dissertation there were two proposed research questions:

- **What are the indicators associated with the students' digital footprint in Moodle that can better measure their learning paths?** The learning path indicators found during the analysis of the already existing literature as well as the study of Moodle's architecture allowed us to establish nine indicators present on the students' digital footprint. Moreover, all those indicators can be tracked for the average student in class, enabling comparison between the students' behavior and the average behavior of the students enrolled in the UC enabling the students to better monitor their learning process. Even though all the indicators intertwine with each other, they were divided into three categories to understand the main focus of that indicator. The indicators found were the following: content accessed by week and by type; assignment delivery delay; best quiz grade, learning speed, consolidation, learning progression, forum participation by week; number of participations on forums. During the development of the platform, some indicators were grouped into the same visualization object, such as tables or charts, for example, the best quiz grade, learning speed, and consolidation were grouped into a table together. Afterwards, with the questionnaire that was used to validate the platform, we could identify that the participants found a set of indicators to be better than the rest. The indicators that were considered most valuable by the participants were the content accessed by week and by type, best quiz grade, learning speed, consolidation, and learning progression. Moreover, when analyzing the platform 87.5% of the participants agree that the platform would have a positive impact on their academic performance (66.7% agree and 20.8% strongly agree), ensuring that the indicators chosen are important to be monitored.
- **How can we visualize students' learning paths during the UC with their digital footprint?** The solution found to visualize the learning path of students through their digital footprint was made with the development a visualization platform. It utilizes a frontend showcasing the indicators proposed and extracted from the behavior that students have while using Moodle. A dashboard with the different indicators was built and the learning path of the student can be monitored and visualized through its analysis.

7.2. Limitations

During the development of this dissertation, several limitations were encountered, which warrant discussion. These limitations pertain to both the availability of learning path indicators and constraints related to the learning path visualization platform.

- **Availability of Learning Path Indicators -** One primary limitation observed in the context of learning path indicators is the scarcity of information. This absence of information comes from two primary sources. Firstly, Iscte's Moodle does not store certain valuable indicators, such as students' class attendance. Secondly, not all aspects of a student's learning journey can be tracked solely through online means, more specifically one platform. While this Moodle analysis can provide insights into a student's interactions with the platform during their studies, it cannot capture activities conducted through alternative methods or offline learning. For example, if a student uses other learning platforms, or utilizes offline resources, or downloads course materials without subsequent online interaction, this falls beyond the platform's monitoring capabilities.
- **Limitations of the Learning Path Visualization Platform -** Despite the scalability of the learning path visualization platform that was created, some inherent limitations exist. The platform's design incorporates the use of stored procedures for data extraction. This approach requires manual installation of these procedures onto the Moodle client's database. Additionally, if future database versions or alterations in information requirements occur, new stored procedures must be created. This reliance on stored procedures may pose challenges in terms of maintenance and adaptability.
- **Validation Limitation** – It is important to note that this platform was developed during the academic year of 2022-2023. As a result, it was not feasible to conduct real-world validation in a live educational setting where students could actively utilize the platform over an entire semester. Instead, a questionnaire was employed to assess the potential utility of the platform without the benefit of real-world usage within a course.

These limitations, while noteworthy, provide valuable insights into the constraints faced during the development of the learning path visualization platform.

7.3. Future Work

While the development of this platform has introduced several essential features for monitoring students' learning paths, there are specific areas that warrant further enhancement. The following suggestions present opportunities for refining existing features and introducing novel functionalities:

- **Enhance User Interfaces** - A thorough analysis of questionnaire responses reveals potential refinements in the platform's user interface. These improvements aim to enhance the accessibility and comprehensibility of the information presented, catering to a broader range of users.
- **Integration into Other Platforms -** The dashboard crafted during this thesis holds promise for even greater utility if seamlessly integrated into a learning management platform. Given Moodle's adaptability through plugins, a strategic approach could involve developing a plugin to facilitate the smooth incorporation of this dashboard, thereby extending its reach and impact.
- **Teacher's Perspective -** In addition to empowering students to monitor their learning paths, it is equally important to provide educators with the tools to oversee the collective learning journey within each UC. The creation of a "Teacher View" would empower instructors to gain valuable insights into how students engage with course materials, fostering more effective pedagogical strategies.
- **Platform Infrastructure Enhancement -** As previously noted, a plugin-based approach emerges as a viable strategy for platform implementation. This approach not only makes it easier to integrate into different Moodle installations but also strengthens the platform's infrastructure, ensuring scalability and robustness.

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Appendix

Appendix A – Questionnaire to validate the platform.

Learning Path Visualization Platform

In this questionnaire you will be asked questions about your familiarity with learning management systems (LMS) as well as questions about a platform that was developed to visualize and monitor the learning path of students.

* Indica uma pergunta obrigatória

1. What is your age: *

   Marcar apenas uma oval.

   - 17-19
   - 20-22
   - 23-25
   - More than 26

2. What is your current educational status? *

   Marcar apenas uma oval.

   - Undergraduate Student
   - Graduate Student
   - Doctoral Student

LMS Familiarity

Here we are going to ask questions about your familiarity with lms platforms, how you interact with them, and the use of certain functionalities.

Figure A.1 – Questionnaire to validate the platform (I)

3. How familiar are you with using Moodle or other Learning Management Systems (LMS)? *

Marcar apenas uma oval.

- Very Familiar
- Familiar
- Somewhat Familiar
- Not Familiar

4. How frequently do you use Moodle (or other LMS) for your studies? *

Marcar apenas uma oval.

- Daily
- Several times a week
- Once a week
- Rarely
- Never

5. How useful do you consider having access to detailed insights about your learning activities on Moodle (or other LMS)? *

Marcar apenas uma oval.

- Very useful
- Useful
- Neutral
- Not useful
- Not very useful

Figure A.2 – Questionnaire to validate the platform (II)

6. How likely are you to use a platform that visualizes your learning activity on Moodle (or other LMS)? *

Marcar apenas uma oval.

- Very Likely
- Likely
- Neutral
- Unlikely
- Very Unlikely

Platform Validation

Here we are going to ask you questions about a platform to visualize students learning that was developed, we want to get feedback on its features and functionalities.

7. Which specific features of the platform do you find most valuable? (Select all that apply) *

Marque todas que se aplicam.

- [ ] Engagement: Tracking Interactions with UC Online Learning Contents
- [ ] Number of Interactions with Different Learning Contents
- [ ] Quiz Grades
- [ ] Delay in Assignment Delivery
- [ ] Forum Participation: Tracking Student Activity by Week
- [ ] Quiz Stats
- [ ] Forum Stats

Figure A.3 – Questionnaire to validate the platform (III)

8. How useful is having access to the average Moodle behavior of your classmates * in a course to be able to compare yours with theirs?

Marcar apenas uma oval.

- Very useful
- Useful
- Neutral
- Not very useful
- Not useful

9. How intuitive do you find the navigation and user interface of the platform? *

Marcar apenas uma oval.

- Very Intuitive
- Intuitive
- Neutral
- Not Intuitive
- Not at all Intuitive

10. How well does the platform meet your expectations regarding the visualization * of your learning activity?

Marcar apenas uma oval.

- Exceeds Expectations
- Meets Expectations
- Neutral
- Below Expectations
- Does not meet Expectations.

Figure A.4 – Questionnaire to validate the platform (IV)

11. How confident are you in interpreting the data and insights provided by the platform to make informed decisions about your learning strategies? *

Marcar apenas uma oval.

- Very Confident
- Confident
- Neutral
- Not Very Confident
- Not Confident at All

12. Do you believe that monitoring your learning activity through this platform will positively impact your academic performance? *

Marcar apenas uma oval.

- Strongly Agree
- Agree
- Disagree
- Strongly Disagree

Figure A.5 – Questionnaire to validate the platform (V)

13. Looking at the dashboard that was presented to you, how often would you use this tool * to monitor your study in a course?

Marcar apenas uma oval.

- Very Often
- Often
- Occasionally
- Rarely
- Never

14. Overall, how satisfied are you with the platform's ability to help you monitor and * improve your learning progress on Moodle?

Marcar apenas uma oval.

- Very Satisfied
- Satisfied
- Neutral
- Dissatisfied
- Very Dissatisfied

Figure A.6 – Questionnaire to validate the platform (VI)