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Teaching analytics: support for the evaluation and assistance in the design of teaching through artificial intelligence

Ibtissem Bennacer

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THÈSE DE DOCTORAT DE

LE MANS UNIVERSITÉ

ÉCOLE DOCTORALE N° 601
*Mathématiques et Sciences et Technologies
de l'Information et de la Communication*
Spécialité : *Informatique (CNU 27)*

Par

Ibtissem BENNACER

**Teaching analytics: support for the evaluation and assistance in
the design of teaching through artificial intelligence**

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INTRODUCTION

Scientific Background

This PhD work has been carried out within the IEIAH team (Ingénierie des Environnements Informatiques pour l'Apprentissage Humain) of the LIUM laboratory (Laboratoire d'Informatique de l'Université du Mans). The LIUM is located on two sites: Le Mans and Laval site. Since its establishment, the major research themes of the LIUM are Technology-Enhanced Learning (TEL) and Language and Speech Technology (LST).

The main scientific project of our team is to elaborate a scientific basis for the development and engineering of TEL systems. The team's actions are structured around this objective, both in terms of research and development. Its research is led according to three primary dimensions:

- **Design, Operationalization, Adaptation of Pedagogical Situations:** a key objective is to integrate teachers and instructors into the design process of TEL systems.
- **Modeling the Observation of Usage Tracks and their Analysis:** this dimension focuses on the analysis of learning situations, relying on teachers' and students' traces in TEL systems.
- **Advanced and Collaborative Interactions for Learning:** it investigates advanced interactions for learning (interactive tables, mixed reality, tangible interfaces, ...) particularly in the context of Serious Games.

The research exposed in this manuscript is fully in line with the second dimension since it addresses the analysis of traces relating to Le Mans University TEL environment (Moodle-Umtice-).

Context

Improving the way of teaching and learning has become a key objective in education today. In higher education, offering personalized lifelong learning, while simultaneously

increasing the number of learners, implies the implementation of new learning practices such as blended learning (face-to-face and distance) or the use of TEL environments such as Learning Management Systems (LMS).

The trend of using LMS is now spreading quickly across all areas of education (Setiawan et al. 2021), with an acceleration observed during the COVID-19 pandemic. Most universities offer LMSs as a “one size fits all” technology solution for all teachers of any discipline. Teachers are also increasingly using these systems instead of adopting pure traditional methods to adapt to the evolution of technology and facilitate learning (Adzharuddin et al. 2013). As a matter of fact, LMS provide a great flexibility in terms of time and space, they support advanced student-teacher interactivity and facilitate the reuse of resources. These platforms can be used by teachers to ease the implementation of their practices, manage courses and learners, and even collect user data and provide reports to management. The latter allow the capture of large amounts of quantitative data regarding the individual behavior of users and designers in the online domain. Considering Le Mans University, Umtice (Moodle) is the LMS used as a techno-pedagogical environment to support the teaching-learning process mainly in face-to-face settings. It has been widely adopted by most of teachers (about 640 teachers and teacher-researchers) and students (about 12,000 students per year) for 15 years.

On the other hand, to ensure a proper use of LMS and a pedagogical fit (better align the tool with teachers’ pedagogy), most universities have established Digital Resource Centers (DRC) to (i) help teachers who want to set up face-to-face and/or online training systems and (ii) offer them a variety of support services: training, pedagogical support and technical assistance. Therefore, they hire pedagogical engineers (PEs) to help teachers to develop, enhance and diversify their pedagogical designs as well as their mastery of LMS and e-learning tools. Nowadays, this professional skill (pedagogical engineering) is developing especially with the integration of techno-pedagogical environments, but it is still poorly documented (Daele 2014).

Within this context, in France, the Ministry of Higher Education launched the HyPE-13 project ¹(HYbridation et Partage des Enseignements or Hybridizing and Sharing Teachings in English) in November 2020. Carried by a consortium of 12 french universities, it aims to accompany teachers and students with new learning devices promoting the hybridization of training.

1. <https://organisation.univ-pau.fr/fr/labels/le-projet-hype-13.html>

Research problem

Despite the growing trend for LMS to facilitate educational activities, the number of teachers using it is not increasing as quickly as one might have imagined (Wang et al. 2009), and many teachers face several difficulties to integrate these platforms into their practices. The main problems of teachers appear to be technical or organizational, due to the lack of support and the lack of time devoted to its learning (Nashed et al. 2022).

During the COVID health crisis, educators across the world had no other option than to switch from traditional to online teaching using LMS among other systems. This highlighted many challenges teachers faced previously and that have been exacerbated by COVID. In particular, the lack of official supervision, policy, conceptual clarity regarding distance teaching and technical skills have been the most discussed issues recently (Mohammadi et al. 2021; Douali et al. 2022). Furthermore, the DRC still struggles to carry out their missions with only few pedagogical engineers (PEs) compared to the teacher population (e.g. there are 6 engineers for 630 teachers in our university). They also lack insights into teachers' competencies, while teachers are not always aware of features TEL systems, such as an LMS, offer.

In psychology, self-reflection is considered as an extremely powerful way to improve a practice when one can reflect objectively (Van Seggelen–Damen et al. 2020; Morin 2011). It enables individuals to move from simply experiencing to understanding. Therefore, it promotes an increased level of self-awareness and consciousness of practice which allows to identify areas for improvement as well as those of strength (Duval et al. 1972). This process motivates people to self-evaluate in order to improve their practices. Yet, studies on technology integration and improving teachers' mastery and use of TEL systems have not placed much emphasis on supporting this outcome.

Therefore, we intend through this research to:

- Provide teachers with personal and social awareness tools to engage them in an LMS learning process.
- Assist them in these situations to improve their LMS use.

To achieve these objectives, three research questions were identified:

1. How can teachers be supported to self-reflect, be aware, and self-evaluate their LMS use?
2. How can we assist teachers to enrich their use of the institutional LMS?

3. What is the most effective method to provide teachers and pedagogical engineers with a support tool while increasing its appropriation?

These research questions seem relevant to achieve our goals. By answering the first one, we believe that the teacher would engage in a learning process to improve their practices in the LMS. The answer to the second research question allows to help and support teachers in this learning. Finally, the adopted method as an answer to the third question should provide teachers and pedagogical engineers with a support tool that fits their expectations. We therefore attempt throughout this work to answer the three previous questions.

Motivations

In the domain of educational sciences, a pedagogical scenario is a written, structured and shareable formalization of what a teacher plans to do or has done (Villiot-Leclercq 2007). However, in the field of computer science applied to education, the concept of scenario is seen as an ordered set of activities, governed by actors who use and produce resources (Paquette 2005). Thus, the way in which the teacher carries out their professional activity and implements a pedagogical scenario represents a teaching practice (Altet 2002). There are many teaching practices. Among the most widespread ones: project-based approach, flipped classroom, block release training, etc.

The present work is motivated by an initial preliminary study concerning the pedagogical scenario of teaching practices in LMS (Bennacer et al. 2021a), which aimed to:

- Measure the relevance of a pedagogical scenario to a given teaching practice.
- Automatically identify a particular teaching practice based on LMS data.
- Assist the teacher in scripting pedagogical practices on an LMS.

Following a preliminary quantitative analysis and interviews with three pedagogical engineers, we realized that:

- Few teachers use new teaching practices. Most of them prefer traditional methods.
- The university LMS is not used to its potential. Many teachers do not use it or it is simply used as a file depository.
- There is no existing formalisms to implement a teaching practice on an LMS.

Consequently, our initial objectives have become unattainable as it is very complicated to detect teaching practices and their relevance since there are only few teachers using

them. Hence, we have seen how crucial it is to promote the use of LMS among teachers and to help them to integrate it into their teaching practices. This will not only allow the evolution of the teaching-learning process through a technological integration, but also eventually enable the investigation of pedagogical scenarios of courses on LMS.

Contributions

To answer our research questions, we leveraged teaching analytics (TA) to analyze teachers' behaviors and assist them in using LMSs. At first, we proposed a methodological contribution that consists of a cycle TOM^{++} composed of 4 stages and a validation layer involving experts (pedagogical engineers) and users (teachers and pedagogical engineers).

We then designed a model for teacher self-evaluation based on (i) a qualitative analysis through interviews we had with several pedagogical engineers and (ii) a quantitative analysis we conducted on four years of teachers' activities on the University's LMS. The intersection of these two studies' results were mined to design an axis-based model that categorizes teachers' use of the platform in order to allow them to assess their practices along several dimensions: **(i)** evaluation (tools used by the teacher to evaluate their students), **(ii)** reflection (tools allowing teachers to collect students' feedback), **(iii)** communication (means of communication used by the teacher), **(iv)** resources (diversity of resources that the teacher makes available to students), **(v)** collaboration (tools promoting collaboration between students) as well as **(vi)** interactivity and gamification (interactive or playful activities used by teachers).

Subsequently, we defined two teaching analytics (TA) metrics: LMS usage trend and usage scores. The first one is based on a clustering analysis that identifies groups of teachers with a particular usage along each axis. To complete the results of this clustering analysis, we proposed two usage scores. They express particularities of use such as curiosity (diversity of functionalities used per axis) or homogeneity (regularity of functionalities' use by axis in relation to a teacher's courses) of each teacher in order to provide a rich support for self-awareness and self-evaluation.

In order to help teachers to improve their overall use of the LMS, we provided three recommender systems (RSs): a RS of unexploited features, a peer RS and PEs RS. The goal of the former is to encourage teachers to discover and exploit the different functionalities of the university' LMS. Thus, for each axis, we invite the teacher to consider the unused functionalities of the axis that could be useful to improve their teaching practices.

The peer recommender system suggests 3 teachers for each axis based on the usage scores we designed (the curiosity score and the homogeneity score) and taking into account the physical proximity between them (university location and teaching department) as well as their specialties. Finally, we recommend to contact pedagogical engineers to get an assistance in the use of the LMS.

Based on a user-centered approach, we have developed a web application named iTeachApp to instrument our model, indicators and recommendations. The application has been experimented at our university to study its usability, utility and appropriation by teachers. The results showed that teachers were interested in adopting iTeachApp and found our proposals relevant. However, this experimentation also revealed a lack of understanding of various terms we used. At the same time, it provided insights to improve our application and proposals (model, indicators and recommendations).

Thesis structure

This manuscript is structured in five parts as shown in figure 1: introduction, state of the art, towards a teaching analytics tool, application and experimentation as well as conclusion.

The state of the art is structured in three chapters: “Learning management system”, “Technology integration among teachers” as well as “Learning and teaching analytics”. We therefore start by presenting the LMSs that are the focus of our work in order to investigate their origins, the existing ones and, above all, the issues faced by teachers when using them. Then, we explore factors affecting the acceptance and usability of LMSs by teachers as well as existing methods to facilitate the integration of technology among them. Finally, we discuss teaching and learning analytics that have emerged to improve education. We explain the difference between them and focus on teaching analytics (TA) that are recent in order to identify existing gaps in literature.

The second part “Towards a teaching analytics tool” is also composed of three chapters: “Methodology”, “Teachers’ behavioral model” and “Model exploitation”. The first chapter proposes a methodological approach to conduct the different phases of this research. The second chapter details the quantitative and qualitative analysis that we have carried out and presents the behavioral model we have designed. The last chapter details the exploitation of the model by presenting its teaching analytics (TA) indicators and the recommender systems we proposed.

Within the application and experimentation part, we present in the first chapter “iTeachApp application” our web application we developed following a user-centered approach. Then, we detail in the second chapter “iTeachApp experimentation” the experimentation carried out at the scale of our university to study its usability, utility and appropriation by teachers.

In conclusion, we present an overview of our research work in this thesis and outline our perspectives.

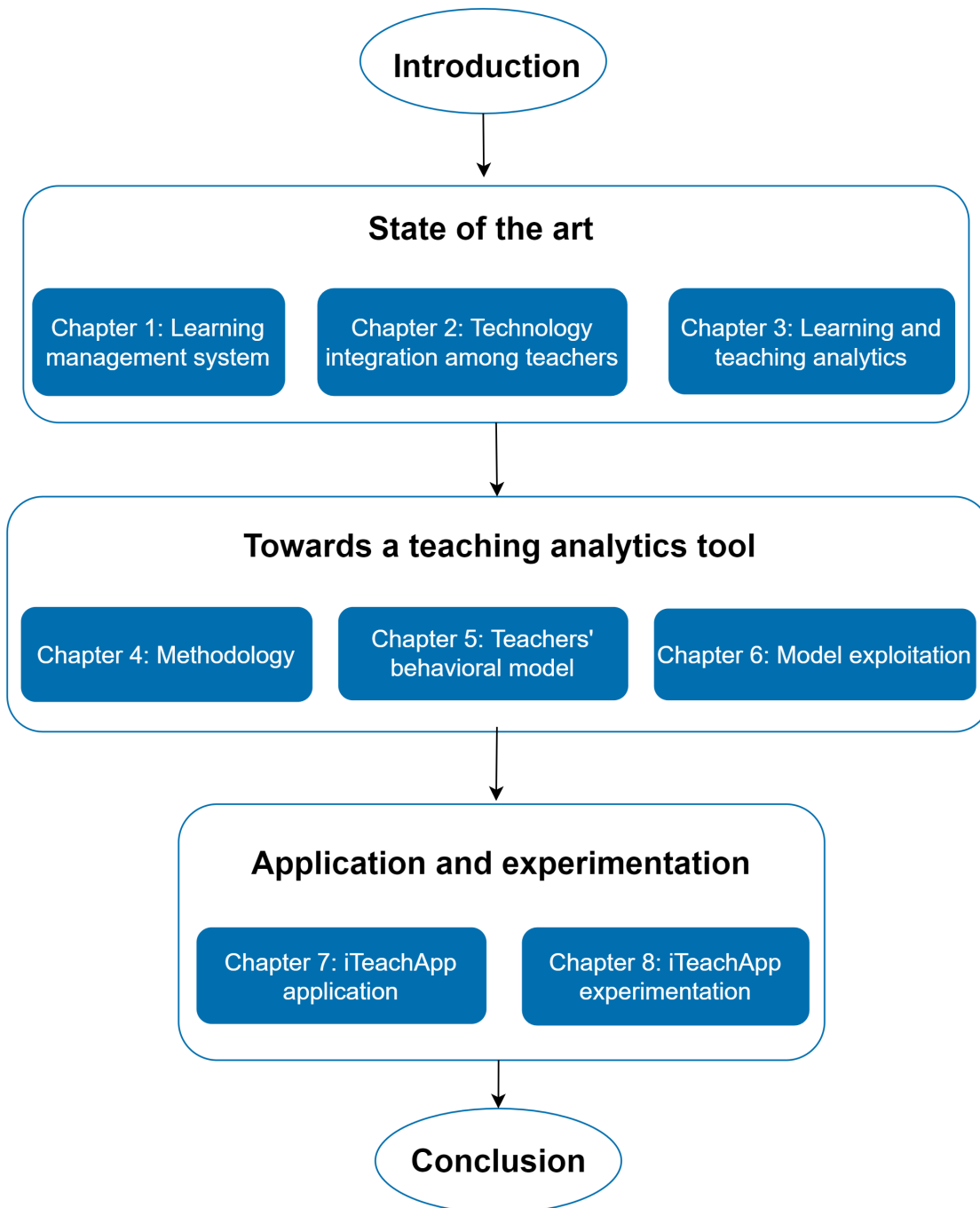


Figure 1 – Outline of the manuscript.

PART I

State of the art

LEARNING MANAGEMENT SYSTEM

Higher education institutions face several challenges in maintaining the quality of academic programs and making important changes to their teaching, learning, and research processes (Anshari et al. 2016). These challenges include the mastery of teaching processes in order to adapt to the evolution of pedagogical objectives, such as the ability to learn in a collaborative and autonomous way, as well as the widespread use of information and communication technologies (ICT). Policymakers around the world believe that integrating ICT into schools should lead to significant learning and teaching outcomes (Jimoyiannis et al. 2007). For this reason, education systems are expected to strategically adapt and create new learning opportunities through the benefits of ICT to broaden students' choices in the academic process and also to provide teachers with an efficient and enhanced way to deliver their courses (Asamoah 2021; Jimoyiannis et al. 2007). There are many types of ICT-driven education tools such as video conferencing, email, multimedia and telecommunications products, etc. Among ICT, TELs are at the core of educational technologies and among them, learning management system (LMS) is one of the most used and deployed (Asamoah 2021).

In this chapter, we explore LMSs and their evolution. Then, we describe their features and the benefits of using such platforms. Finally, we outline their limitations with a focus on problems experienced by teachers when using them.

1.1 Definition

While the literature provides several definitions of an LMS (McGill et al. 2009; Piña 2012; Lopes 2014; Xin et al. 2021), they all fit into a similar concept. (McGill et al. 2009) considered the LMS to be “an information system that facilitates e-learning and processes, stores and disseminates educational material and supports administration and communication associated with teaching and learning”. From a technical point of view, (Piña 2012) defined LMS as “a server-based software program that interfaces with a database

containing information about users, courses and content”. On the other hand, LMSs have been described by (Lopes 2014) as “a web based or cloud based software program which assists in teaching learning process and helps in effective delivery of instruction, training and development program”. Whereas recently, (Xin et al. 2021) defined an LMS as “an online portal which is used to connect lecturers and students. It is a place where class material and activities can be shared easily. It is also a portal where lecturers and students can communicate and have interactions aside the classroom”.

All these previous definitions present the LMS as an IT system which assists universities and institutions in the teaching and learning process. We have also noticed a constant technical evolution that fits the new LMS in the current technological environment. Therefore, we propose to define the LMS as “**a platform that aims at improving teaching methods and facilitating students’ learning, through a range of administrative and pedagogical services related to educational settings**”. In essence, its key features are the online training deployment and tracking, courses and learners management as well as users’ actions’ tracking and reporting.

1.2 Evolution

Modern LMSs draw inspiration from a variety of inventions and innovations from the past. Hence, this section presents their origins and the most common LMSs currently in use.

1.2.1 History

In this subsection, we explore key milestones in the history of the LMS and provide examples of machines/tools that had a direct impact on the way LMSs are operating today (Kuchkarbaev 2021; Lopes 2014; Cheng et al. 2010).

- **1929 – Testing machine:** Sidney Pressey, a professor at Ohio State University, built a teaching machine in the 1920’s and appointed it “Testing machine”. Resembling a typewriter, it offered various kinds of practical exercises and multiple-choice questions with learners having to drill in answers which were recorded at the back of the machine. The learner could only progress if their answer to the previous question was correct - a feature that most modern LMSs still use.

- **1956 – SAKI:** The SAKI or Self-Adaptive Keyboard Instructor was the first machine to offer a slightly personal learning experience. It was created by Gordon Pask and McKinnon Wood in 1956. The software was designed to continuously monitor student performance and generate practice exercises for users based on that performance. More specifically, it customized questions based on the learner's performance and added difficulty levels as the learner's performance improved.
- **1960 – PLATO:** Urbana-Campaign Illinois University has developed the PLATO (Programmed Logic for Automated Learning Operations) system. It was a computer-based training program and the first platform to operate within a learning community and enable collaborative learning through its instant chat and email functionalities. PLATO allowed users to type and interact through a host of networks, assigning lessons, learning independently, and monitoring lesson/student progress.
- **1983 – Project Athena:** Almost a forerunner to the LMS, the project Athena from MIT in 1983 created a distributed computing environment by setting up workstations. In other words, it allowed learners and instructors to access files from any computer on the MIT campus.
- **1990 – FirstClass:** FirstClass is known as the first real LMS, it is still in use today. It was released by Softarc in 1990 for the Macintosh platform. It provides access to private e-mail and public forums, thus allowing students to ask questions and clarify the theoretical material presented in the learning modules. It also offers access to a variety of home desktop users, not just mainframe ones.
- **1997 – Interactive Learning Network:** Interactive Learning Network was developed by CourseInfo in 1997. It was the first LMS to use a relational MySQL database. It was installed on several campuses, including Cornell University and Yale Medical School.

Since the appearance of the first LMSs with the Athena project and FirstClass in 1990, the technological potential of these platforms have never ceased to increase, especially with the arrival of the cloud and the SaaS (Software as a Service) architecture in 2012. The latter provided universities and companies with access to the full suite of tools via the web without installing a single additional piece of software on a local PC or mainframe. Many LMS applications have also begun to support delivery to mobile devices using Wi-Fi. On the other hand, we realize that studies on the history and origins of LMSs focus much more on the technological side with less interest in the pedagogical side. However, the latter

has also evolved several times, starting with the first LMS with limited functionalities (share and access files only) and ending with nowadays' LMSs that offer a variety of functionalities aiming at facilitating and improving the teaching and learning process, that will be covered in the section 1.3.1.

1.2.2 LMSs nowadays

Today, there are many LMSs at the disposal of companies and universities. Figure 1.1 shows the results of a study across four global regions based on their academic LMS market share¹ published in spring 2017 by e-Literate, an organization devoted to help higher education and education companies improve their efforts to get more students to succeed in a 21st century world.

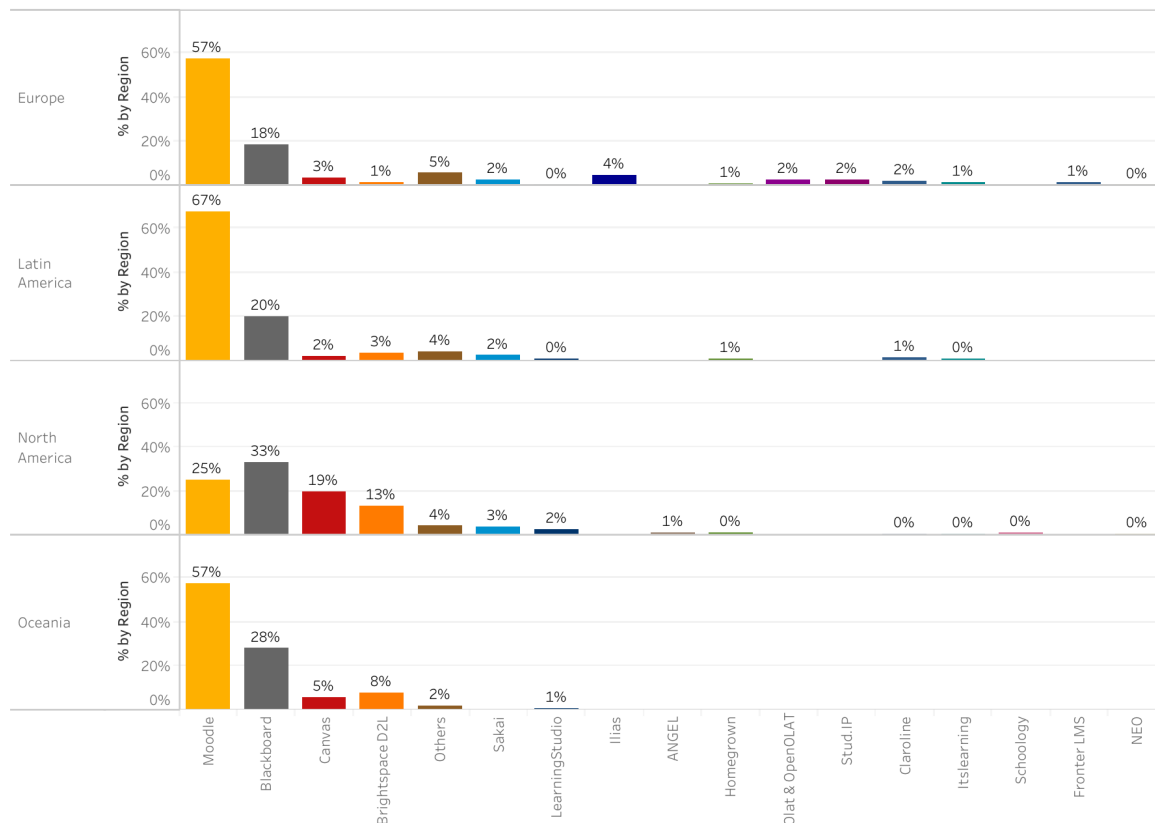


Figure 1.1 – LMS market share in 2017 across four global regions¹.

Moodle dominates the LMS market in Europe with 57%, Latin America with 67%

1. <https://eliterate.us/academic-lms-market-share-view-across-four-global-regions/>

and Oceania with 57%. In North America, Moodle is in second place with 25%, behind Blackboard, whose market share is 33%. Thus, we describe here Moodle and Blackboard since they are considered as the most popular LMSs in the world.

- **Moodle**²: In 2002, Moodle (Modular Object-Oriented Dynamic Learning Environment) was introduced to the public. It remains one of the most popular open-source LMSs available online (see an example of its interfaces in figure 1.2). It allows to create a personalized learning site accessible from multiple devices. Some repetitive tasks, such as registration, can be automated with dynamic rules. It also facilitates students' access to personalized courses and programs, track their progress and receive their grades and certifications. Furthermore, participants can access their messages and a collaborative workspace. Several other features can be added to the basic system through plugins. Moodle is integrated into the surrounding digital ecosystem through two standards: SCORM³ and LTI⁴. These contribute to better interoperability and increase the scope of its functionalities.
- **Blackboard**⁵: it is a private company that provides technological solutions for education. It was conceived to be an instructor-centered platform. It is mainly a place where the instructor can upload course material and collect student learning. This system is a licensed product, and the price of it depends on the needs of the institution. Blackboard can not be integrated with other systems but it offers wide range of tools and services (see an example of its interfaces in figure 1.3).

There are many other LMSs besides Moodle and Blackboard, such as: Canvas, D2L, TalentLMS, Sakai, ANGEL, ATutor, SuccessFactors, SumTotal, Litmos, etc. (Ferretti et al. 2018; Kasim et al. 2016). These platforms have a large number of functionalities in common, with standard features such as course creation, content hosting, online assessments, and reporting. Hence, the choice of an LMS depends on the specific needs of the university/company, their financial capacities as well as the requirements of teachers.

For example, if we compare Moodle to Blackboard, we notice that they share many features like any other LMS but each one has its own philosophy. Moodle is an open source LMS that is constantly being analyzed and updated to provide personalized training to

2. <https://moodle.org/?lang=en>

3. Sharable Content Object Reference Model, it is a set of standards for learning technologies that allows the specification of parameters on content packaging and metadata.

4. Learning Tools Interoperability, it is a standard for integrating rich learning applications. It aligns learning resources and activities from other sites.

5. <https://www.blackboard.com/fr-fr>

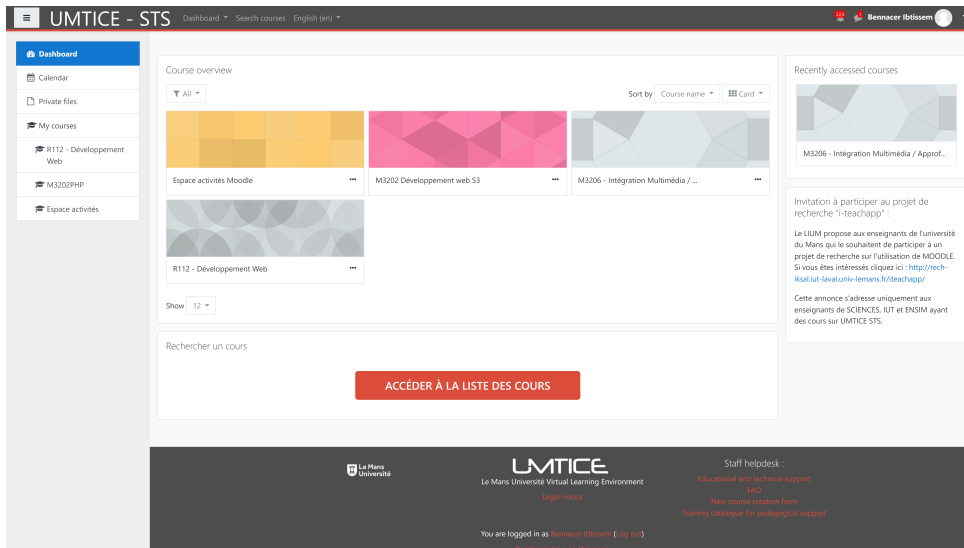


Figure 1.2 – An interface of Moodle at Le Mans university in France.

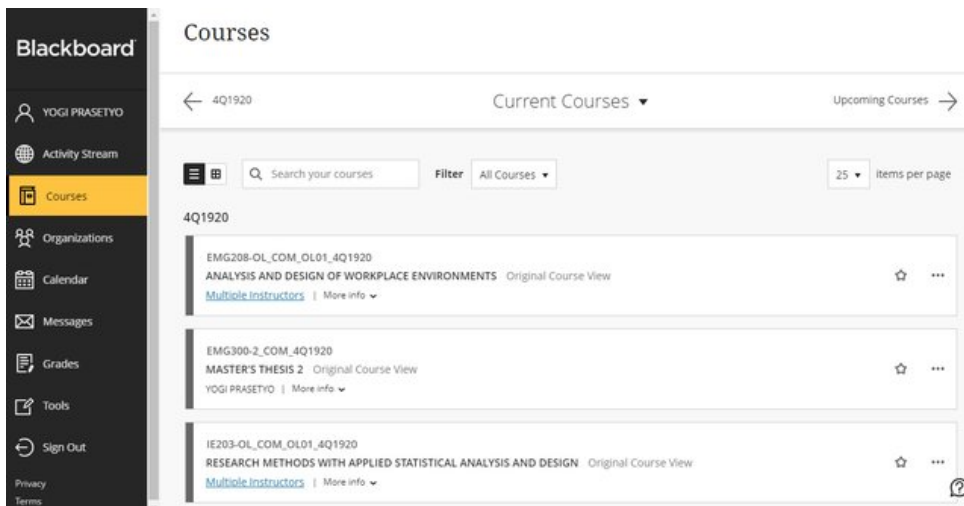


Figure 1.3 – An interface of Blackboard at a private university in the Philippines (Prasetyo et al. 2020)

its learners. It also benefits from the ability to integrate many plugins which make each Moodle different from the other but its user interface is not simple to use. Moreover, since Moodle is free, it can be easy to acquire one but its configuration is time consuming⁶. In contrast, Blackboard is a commercial project and the platform is closed-source, so all development is undertaken by the parent company. This means that there is less flexibility in terms of developing new features, plugins or software integration but it is considered as much more easier to use.

1.3 Features and benefits

1.3.1 Features

Based on existing literature (Wichadee 2015; Kasim et al. 2016; Srichanyachon 2014), LMS features or tools can be classified into three main categories: learning tools, communication tools and productivity tools as detailed in the figure 1.4.

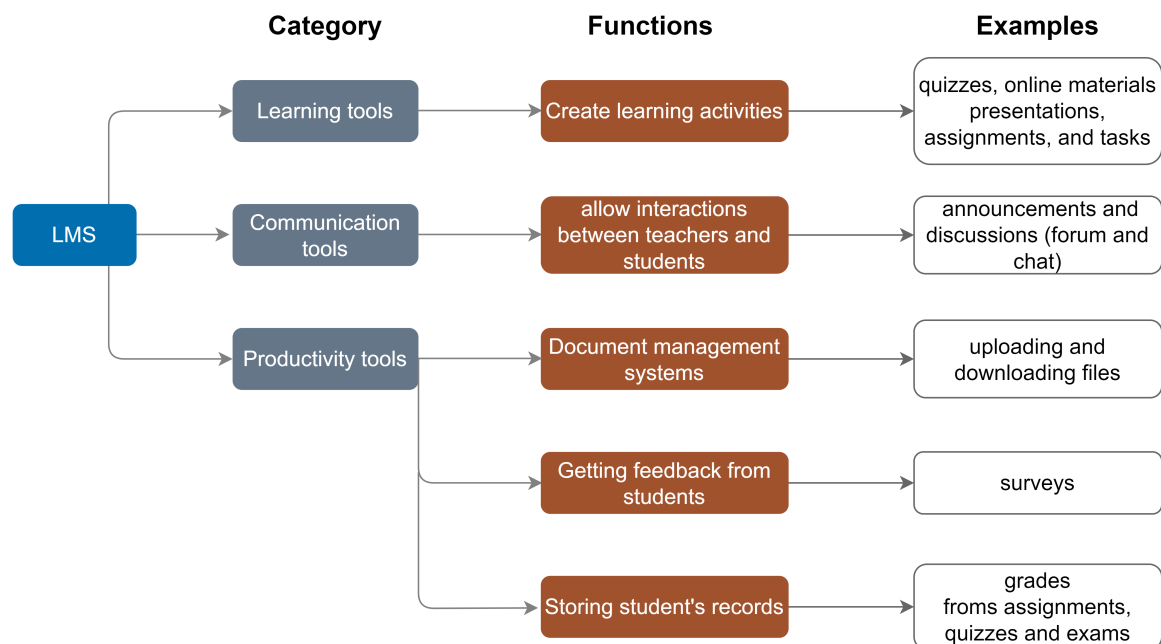


Figure 1.4 – LMS features.

6. <https://www.paradisosolutions.com/blog/moodle-vs-blackboard-lms-comparison/>

The first category involves tools for creating learning activities to provide students with relevant content or to assess their skills. It covers quizzes, online materials presentations, assignments, games, and tasks. The second category is intended to enable and promote interactions between teachers and students or among students themselves. The most common communication tools are announcements and discussions (forum and chat). On the other hand, the productivity tools category includes document management systems that allow teachers and students to upload and download files. It also covers other management tools which prove teachers with access to information about students' skills such as surveys. Moreover, it includes tools that enable students to visualize a report of their overall performance, such as grades for each assignment, quiz and exams. It should be mentioned that some features can fall into more than one category, such as quizzes that are part of the learning tools but also store students' records, thus belonging to the productivity tools as well.

LMSs have a wide variety of features, especially with the possibility to add plugins that allow the development of custom features. Thus, we believe that LMSs are now considered as complex a software package as Photoshop, which requires training to master it. The technical evolution might not be as problematic for the user as the pedagogical evolution. Today, many pedagogical features are complicated for the users: some of them overlapping (e.g. two activities that share quite the same objective), others with complex settings (e.g. quiz) and many administrative ones that are not obvious for users (e.g. notion of question pool that can be shared, cohort of students, fine activity visibility tuning according to the user profile, etc.). Therefore, LMS functionalities have to be specific and familiar to both teachers and students. In particular, it seems that teachers would have more confidence in teaching an online course if they feel that the LMS is an appropriate environment for learners and easy to use (Demir et al. 2021).

1.3.2 Benefits and adoption

Understanding the potential benefits of adopting an LMS is relevant to education. In the literature, most authors agree on some advantages of using an LMS (Bradley 2021; Lopes 2014; Gautreau 2011).

- The major asset of LMS is to involve all stakeholders within the institution in the training process (instructors, learners, administrative staff, human resources, managers).

- For instructors, LMSs offer the benefit of being able to host all of their courses and learning resources within a single platform.
- LMSs have a statistical tracking tool that allows them to collect data related to courses. The pedagogical team can therefore know the time spent by the learners on the platform, the number of course modules they have taken and their results in evaluations.
- The learning material is more engaging, so users learn more. For instance, using gamification in an LMS aims to keep them interested and motivated.
- LMS is one of the most cost-effective solutions in higher education because it can reach a large, globally dispersed audience in a short period of time with consistent content delivery.

For the above-mentioned reasons, a growing number of educational institutions around the world have begun to leverage LMS platforms to provide a more effective way for students to learn. According to a study by (Piccioli 2014) in 2014, the highest growth rate for e-learning was found in Asia, where it reaches 17.3% on an annual basis, followed by Eastern Europe (16.9%), Africa (15.2%) and Latin America (14.6%). Figure 1.5 depicts this growth rate by country (Pappas 2015).

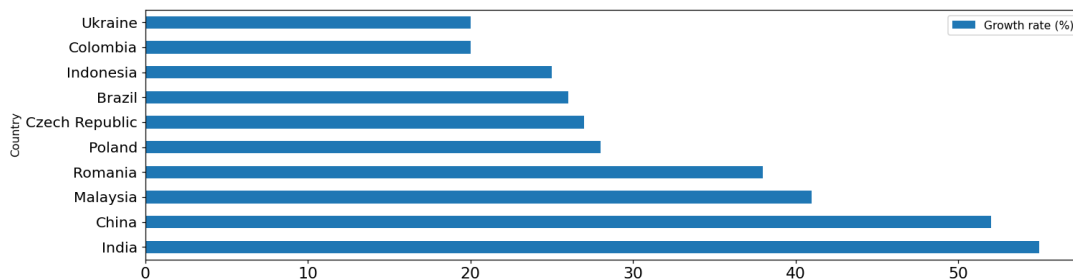


Figure 1.5 – Top 10 growth rates of e-learning by country (Pappas 2015).

The increased adoption of learning technology solutions across the corporate sector is driving the growth of the e-learning market. For context, (Pappas 2015) studied the LMS market in 2013 and found that it was worth \$2.55 billion with an estimated compound annual growth rate of about 25.2%. The LMS market, therefore, was expected to be worth about \$4 billion in 2015 and over \$7 billion in 2018. The largest proportion of revenue contribution was expected to be generated in North America. A second study used market

size data from 2016 to 2021 to predict the growth of e-learning platforms in 2024⁷. The results show that the market size is expected to reach \$100B in the education sector and \$60B in large enterprises (figure 1.6).

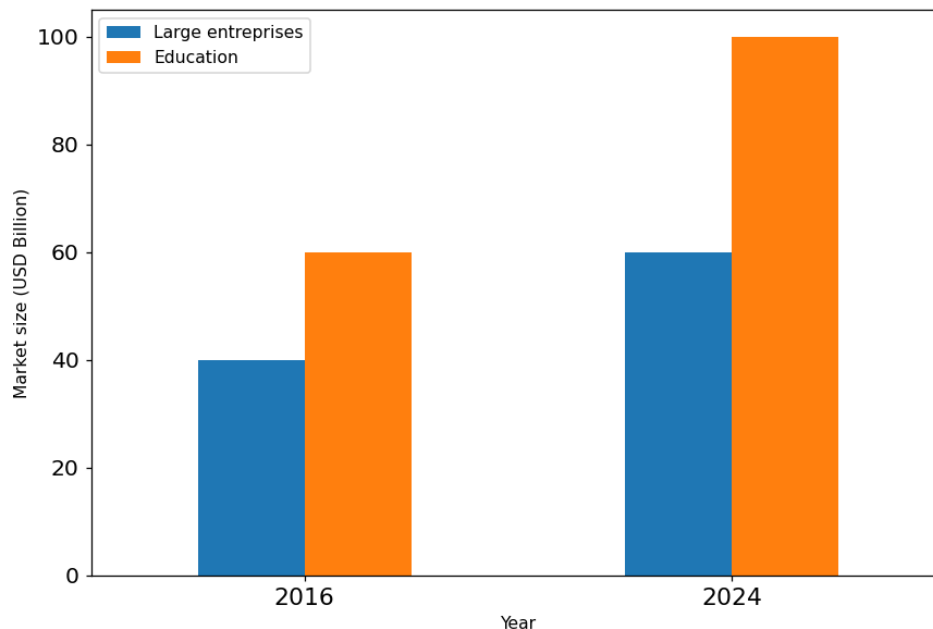


Figure 1.6 – Global e-learning market size⁷.

Due to the COVID-19 pandemic, many schools, colleges, and universities were forced to close in order to contain the virus. As a result, education systems embraced e-learning to assist students remotely during the epidemic. Thus, the use of LMSs has seen a very significant increase by the latter (Douali et al. 2022). However, it is still very early to assume if this increase will last.

On the other hand, according to (Anshari et al. 2016), the LMS can be considered as a strategy to retain existing users and attract new ones. User retention is important for the growth and sustainability of higher education as a service. Organizations are challenged not only to maintain existing services, but also to acquire ubiquitous expertise within the LMS. As education providers are increasingly competitive, the need to manage and deliver better services through an LMS is a strategy that must be carefully planned to avoid failure (Anshari et al. 2016). By 2022, given the increase of LMS adoption by universities and companies, we believe that they are no longer considered as a strategy

7. <https://www.docebo.com/resource/report-elearning-trends-2019/>

to distinguish institutions or to attract users. Nevertheless, the distinction between LMS adoption and usage remains important. Therefore, one key question to ask today is: are these LMSs adopted by organizations exploited to their fullest potential by their users?

1.4 Limitations

1.4.1 General limits

Today's LMSs allow an organization to manage everything related to learning. However, it has several limitations:

- Online learning deteriorates social interactions and reduces their naturalness. Face-to-face courses allow for formal and informal exchanges, while the latter are generally more limited in LMS (Ferretti et al. 2018).
- LMSs tend to be extremely teacher-centric, providing an environment for instructors to manage digital content. However, today's LMS design does not focus on the social-constructivist approach of students in order to support lifelong learning (Ferretti et al. 2018).
- LMSs are complex and need to be socialized (require training and assistance to use it). The focus was mostly on improving the technical aspects of the system, not on its usability. Hence, the most challenging issue with LMSs is that users feel comfortable and familiar with the system (Multazam et al. 2022).
- The number of LMS users was not growing as quickly as expected, although they were considered for a long time as a useful tool to facilitate teaching and learning activities (Wang et al. 2009). A recent study in Russia has confirmed that these issues persist until now (Zharova et al. 2020). The researchers studied the use of LMS based on the opinions of teachers and students. The results showed that LMS was reported by both students and teachers as not being a mean of their active communication. Moreover, the study showed that there was a rather low frequency of LMS use with 43% of students using it rarely and 44% of teachers having the experience of delivering courses on LMS, but despite this, they rarely used it. After COVID-19, they found that when teachers had less prior experience, they experienced more serious problems in the transition to distance education. Table 1.1 represents reasons to resist using LMS reported by this study.

Table 1.1 – Reasons to resist using LMS (Zharova et al. 2020)

Reasons	Opinion that using the system complicates the learning process	Reluctance to spend time on mastering the system	Lack of understanding of the purpose and the benefits of using the system	Lack of motivation to work in the system
Students	29 %	24,6%	39%	31,9%
Teachers	28,6%	42,9%	21,4%	78,%

1.4.2 Teachers' issues

As competition among education providers increases, managing and delivering better services through LMSs requires a carefully planned strategy to avoid potential failure. According to (Anshari et al. 2016), reasons behind failure can be various: non-ready users for e-learning systems, inadequate IT support, poor interface, complicated system and lack of support, etc. Generally, these barriers can be categorized into two levels: school-level and teacher-level barriers (Multazam et al. 2022).

School-level barriers

All external obstacles that affect teachers' mastery of the LMS are included as school-level barriers such as lack of time, lack of effective training, lack of accessibility, and lack of technical support. In this context, (Comas-Quinn 2011) revealed that teachers' main problems involve technical issues, lack of integration and lack of time. They effectively complain about spending more effort on the new technological devices to master them than on reconsidering their own professional identity as teachers within an online environment.

With the COVID health crisis, educators across the world had to switch from traditional to online teaching mode using LMS among other systems, which has increased the obstacles teachers are facing. In particular, the lack of official supervision, policy, conceptual clarity regarding distance teaching and technical skills have been the most discussed issues of late (Mohammadi et al. 2021; Douali et al. 2022).

Teacher-level barriers

Challenges related to teacher traits are among the teacher-level barriers such as teachers' lack of confidence and competence, their unwillingness to change and negative mindset, etc. For instance, (Fung et al. 2012) have shown that generally, the difficulties faced are related to the knowledge and expertise of teachers. The LMS can be used more easily by those experienced in using technology. As a matter of fact, their ability to work around technology enables them to better express their pedagogical vision. In contrast, beginning and novice teachers using technology might find it challenging to express their intentions. While one might think that the younger generation handles new technologies more easily, this skill depends in fact on many other factors. For example, according to (Ozkan et al. 2009), the three characteristics affecting teachers' use of technology include attitude toward technology, teaching style, and control of technology. (Coleman et al. 2017) classified these different factors into two categories: individual and external. Individual factors represent individual characteristics of teachers that include demographic attributes (e.g., age, gender, seniority or status) and technology-related variables (e.g., technological ability and knowledge, previous experience with technology, attitude toward technology, motivation to use technology). In contrast, external factors are related to social effects such as teacher's interactions, group pressure, the teacher's role in the group and the expectations of their superiors, teacher's beliefs and behaviors.

Teachers' use of LMS is not only related to their skills and opinions about technology, it is also dependent on their work environment. Therefore, acting on both levels is important to help them integrate LMSs into their teaching practices. Furthermore, institutional support and assistance (school-level) can help improve their skills and confidence when using such platforms (teacher-level).

1.5 Synthesis

In this chapter, we have investigated LMSs and presented some of the current existing ones such as: Moodle and Blackboard. Each platform has its own specificity and the choice of the right one depends on the requirements and needs of users. All these systems offer a great flexibility in terms of time and space, they promote a great interactivity between students and teachers and facilitate the reuse of resources. When teachers use LMS, it seems that they can more easily implement their practices and manage their courses and students. However, they are considered complex tools whose use is not obvious

to everyone. They therefore need to be well socialized, supported by training and much more documentation (Multazam et al. 2022). On the other hand, some studies have shown that LMSs are not used to their full potential despite their adoption as a complementary tool for education (Zharova et al. 2020; Alshira'h et al. 2021; Demir et al. 2021). Many teachers encounter several difficulties in integrating these platforms into their practices. In particular, their main problems seem to be technical and organizational, due to the lack of support and the lack of time devoted to its learning (school-barriers). Moreover, there are some challenges on the teacher side related to their skills, refusal to change and reluctant mindset (teacher-barriers).

While this minimal use of LMSs may be the technological reality, it is disappointing compared to previous technologists' visions of transforming learning and teaching through these platforms. Accordingly, this thesis addresses the technology issue in an attempt to improve the use of LMSs and support teachers in exploiting its real capabilities.

TECHNOLOGY INTEGRATION AMONG TEACHERS

Technology has made it easier for teachers to create more engaging courses, enhance their skills and use them more effectively. Thus, supporting teachers in using and mastering these tools such as LMS is crucial nowadays for education. However, current works are much more attentive to students while leaving out teachers who also still struggle to improve their courses (Alshira'h et al. 2021). Nevertheless, some studies have focused on exploring factors affecting teachers' use of LMSs by considering their acceptability and usability of such platforms to identify aspects on which actions must be taken to change this situation (Cigdem et al. 2015; Coskuncay et al. 2013; Kopcha 2010; Alshira'h et al. 2021; Demir et al. 2021).

Therefore, to help teachers overcome these challenges related to LMSs, we think it is essential for them to adopt a learners' mindset. In this context, some studies have focused on teacher evaluation using a variety of methods in an attempt to help them to become aware of their LMS use and improve it (Valsamidis et al. 2012; Spooren et al. 2013; Tewari et al. 2015). On the other hand, professional development approaches have been proposed as a mean to enrich teachers' technology skills (Baran et al. 2014).

Accordingly, the present chapter discusses the acceptability and usability of technology by teachers, with particular emphasis on LMS. Afterwards, we investigate teacher evaluation and approaches to support their professional development.

2.1 Acceptance of LMS

In research on user acceptance of different technologies, the most commonly used model is the technology acceptance model (TAM). It was introduced by Davis in 1989 to provide an explanation of determinants of technology acceptance. Thus, it assumes that perceived usefulness (the extent to which a person believes that using a certain system

would improve their performance) and perceived ease of use (the degree to which a person believes that using a particular system would be effortless) are the fundamental factors of user acceptance (Davis 1989), and this has been widely validated empirically (Venkatesh et al. 2000; Yuen et al. 2002).

While taking TAM as the basic model, subjective norm and computer self-efficacy were introduced by (Yuen et al. 2008) to form a composite model to explore teachers' acceptance of online learning technology. Effectively, a person's subjective norm is their perception that most people of importance to them think they should or should not engage in the behavior in question. On the other hand, computer self-efficacy is defined as the judgment of one's ability to use computer technology.

In education, several works have been conducted based on TAM. In general, research on technology adoption showed that teachers' behavioral intention to use the LMS is significantly correlated with self-efficacy, technological complexity, and subjective norm (Condie et al. 2007; Wang et al. 2009).

In the context of an LMS, the subjective norm is defined as the social pressure exerted by principals and other teachers on teachers to use a system (Ajzen 1991). As a result, several researchers have shown the importance of this dimension in changing teachers' intention to use the LMS (Cigdem et al. 2015; Coskuncay et al. 2013). For example, (Cigdem et al. 2015) relied on the conceptual framework proposed by (Coskuncay et al. 2013) which is a model developed by extending TAM, to study the intention of teachers in a professional college. For this purpose, they collected data from 115 teachers via a questionnaire. The latter includes a scale for:

- Perceived ease of use: "Interface of the LMS is clear and easy to understand".
- Perceived usefulness: "LMS increases productivity of the course".
- Behavioral intention and application self-efficacy: "I can use LMS, even if there is no one to help when I get stuck".
- Technological complexity: "It does not take too long to learn how to use LMS".
- Subjective norm: "My colleagues encourage me to use LMS".

Additional external variables were also adopted, including teacher age, previous teaching experience, and the course type. Following a statistical analysis, the results suggest that the subjective norm influences teachers' beliefs about the usefulness of the LMS.

On the other hand, (Kopcha 2010) summarized the barriers and factors that affect teachers' adoption of technology in terms of what they typically lack as follows:

- Time devoted to learn and integrate new technologies.
- Beliefs behind the use of technology for teaching.
- Up-to-date and functional technology as well as support.
- Professional development which reaches further than skill building with technologies such as mentoring, peer collaboration and course design.
- Culture promoting the use of technology and new pedagogical practices adoption.

While studying the acceptance of LMSs can predict teachers' intentions to use these platforms and highlight any barriers affecting their adoption, we think it is not enough on its own. Leveraging these factors is extremely important to reverse their negative intentions and engage them in the LMS learning process.

2.2 Usability of LMS

2.2.1 Definition of usability

ISO 9241-11 provides a framework to understand the concept of usability and apply it when people use systems, products and services. It defines usability as “the extent to which a product can be used by specified users to achieve specific goals with effectiveness, efficiency and satisfaction in a specified context of use”.

Three critical elements are emphasized to represent the usability of a product, they can be defined as follows:

- **Efficiency:** the degree to which the product allows tasks to be performed quickly, efficiently and economically or adversely affects performance.
- **Effectiveness:** the accuracy and completeness with which particular users achieve specific goals in a given environment.
- **Satisfaction:** the degree to which a product gives contentment or satisfies the user.

Usability is one of the most important concepts in human-computer interaction (HCI) research. In order for a software to be considered highly usable, it must be possible to navigate the website or application using previous experiences that have been “received”, “learned” and “stored”, without the need to learn something new (Alshira'h et al. 2021; Demir et al. 2021).

2.2.2 Evaluating the usability of an LMS

Many existing studies have examined the concepts of usability and user satisfaction. These concepts refer to the evaluation of the end-user's interactions with the implemented systems, such as satisfaction, interest, value, effectiveness, benefits and dissatisfaction (Alshira'h et al. 2021; Demir et al. 2021; Mohammad 2020).

There has been a lot of research conducted to evaluate LMS from the students' perspective. However, there is a gap in the literature regarding teachers who are central to the evaluation of LMS (Demir et al. 2021). Several criteria have been used to evaluate an LMS, including:

- **Functionalities:** LMS functionalities are essential and must have specific characteristics that appeal to both teachers and students (Demir et al. 2021).
- **Satisfaction:** this process of finding out whether a user is satisfied with the product is a fundamental aspect of evaluating a product (Demir 2011).
- **Ease of use:** it indicates the simplicity of understanding e-learning systems, the speed of locating content, navigation and the ability of learners to manage their progress (Alshira'h et al. 2021).
- **Accessibility:** it is considered as an assistance function that e-learning systems use mostly to help people with disabilities (i.e. text-to-speech, closed captioning and keyboard shortcuts) (Alshira'h et al. 2021).

Using the latter, (Alshira'h et al. 2021) conducted a case study for universities in Jordan during the COVID-19 pandemic, aiming to explore and develop a new approach to assess the usability of learning management systems. On the other hand, (Demir et al. 2021) sought to better understand how teachers use LMS in terms of user experience and satisfaction through a comparison of three known LMS: Canvas, Blackboard and Moodle. (Mohammad 2020) aimed to evaluate the effects of usability and accessibility on user satisfaction through their study. The results of these three studies indicated that teachers are not satisfied with LMSs. (Alshira'h et al. 2021) analyzed three experts' opinions on the usability and accessibility of LMS platforms sites used in Jordanian universities. They found that users' satisfaction with LMS functionalities was 39.5% and their inability to use them was 76%. Thus, they suggested some improvements to the design of LMS platforms. Furthermore, (Demir et al. 2021) compared teachers' satisfaction level when using three different LMS (Canvas, Blackboard and Moodle). Results showed that satisfaction for Canvas, and Blackboard is identified at C level, where Moodle ended up at D level. Grades

represent the LMS evaluation by teachers and range from A (superior performance) to F (for poor performance), with C indicating “average”. These findings indicate that all LMSs have room for further improvement.

In general, assessing the usability of an LMS provides much more insight into the shortcomings and problems of the tool. Moreover, an in-depth analysis of teaching practices on these platforms is required. Currently, most of these studies are only conducted for the purpose of evaluating teachers (Anagnostopoulos et al. 2021). However, it seems obvious that we cannot evaluate teachers without at least providing them with the necessary training and guidance. Thus, it is important to provide another layer of assistance and support to teachers beyond improving the ergonomics and the functionalities of LMSs. This can help to better encourage teachers to use such platforms, which we consider to be complex due to the number and variety of the functions it offers.

2.3 Teachers' evaluation

As global attention to teacher evaluation increases, policymakers in many countries have turned to new teacher evaluation policies to improve teaching quality (Anagnostopoulos et al. 2021). In this section, we explore teacher evaluation in general and in relation to LMSs, with the intention of identifying the different methods used and studying the effects they may have on teacher practices especially on LMSs.

Teacher evaluation has been defined by (T. S. Almutairi et al. 2021) as the achievements of teachers and what they need to develop or improve in their performance. It is also described as an image that helps educationists, policymakers, inspectors or other stakeholders to get information about teachers and their teaching. For this purpose, (T. Almutairi et al. 2015) conducted a study to investigate teacher evaluation tools considering teachers' perspective. Results showed that observation by heads and inspectors, students' achievement, teachers' portfolio, self, peer and student evaluation either survey or by interview should be used to evaluate teachers' performance. Observation was the preferred approach, and student evaluation was given the least attention. Based on this research, (T. S. Almutairi et al. 2021) used a survey to evaluate teachers in Kuwait. The dataset of this study included teachers, department heads, and high school students from four different districts. Findings showed no significant difference between teacher self-evaluation and department head evaluation. Besides, the study reveals that subjectivism and competition may affect peer evaluation as well as students may overrate their

teachers' performance in an attempt to paint a better picture of their teachers in front of the evaluators. This study emphasizes the fact that teachers can and should be involved in evaluating their own performance, as there is evidence of their ability to do so fairly accurately and in a manner that aligns with the evaluations of their department heads (T. S. Almutairi et al. 2021).

The aforementioned works focus on general teacher evaluation and sum up the various existing methods for doing so. In contrast, there are few studies that focus on the evaluation of teachers' techno-pedagogical performances in LMS. The work of (Valsamidis et al. 2012) is an example for evaluating teachers' techno-pedagogical performances in LMS, with the intention to enable teachers to measure and evaluate their courses. In the literature, an important element in the teaching evaluation process is to ask some form of feedback from students on teaching. Student Evaluation of Teaching (SET) represents a way to get such feedback and aims to constructively use these data for improving teaching practice. Some researchers find that SET data collection and analysis has many advantages, such as giving the teacher an overall synthesis of students' opinions and to respond quickly to their concerns (Spooren et al. 2013). In this perspective, (Tewari et al. 2015) evaluated course content designed by teachers based on student opinions. Then, they proposed a recommender system that analyzes learners' opinions about content and makes recommendations to teachers regarding the modification of a particular part that is difficult for learners to understand using opinion mining. Additionally, (Gottipati et al. 2018) used latent Dirichlet allocation (LDA) models and sentiment mining techniques to quantify and derive insights from student comments in an attempt to improve the teaching process. They focused on students' textual data to discover aspects or topics of the comments. Then, they employed sentiment mining techniques to classify the comments as positive or negative.

While the visualisation of SET could support teacher reflection on teaching practice, countless debates exist about the validity of SET data. In the opinion of (Dean et al. 2015), SETs assess student satisfaction rather than student learning or teaching quality. Moreover, (Hessler et al. 2018) found that student feedback was more favorable when teachers offered chocolates to students in class immediately before student surveys were conducted. Accordingly, many researchers believe that the use of SET data yields biased results, affecting overall credibility of the study outcomes (Dean et al. 2015; Hessler et al. 2018).

Teacher evaluation not only identifies further difficulties faced by teachers but also

motivates them to achieve improvement. However, it is very important to carefully consider and choose the evaluation methods. In this context, (Close et al. 2018) stated, “it is far better to build evaluation systems that educators trust and that align with their beliefs about teaching and learning”. This can be accomplished by including teachers in the evaluation process and giving them the opportunity to choose the method, tool and indicators used for their evaluations. Thus, we believe that self-evaluation is an important way to proceed since it allows teachers to reflect and become aware of their own practices and then act to change and improve them. This fact has been highlighted by sociologists who insisted on the importance of understanding oneself before engaging in any improvement and changing practices (Van Seggelen–Damen et al. 2020; Morin 2011; Duval et al. 1972). This will be the subject of the next section.

2.4 Self-awareness, self-reflection and self-evaluation

According to Aristotle, making a real impact in this world begins with knowing and understanding who we really are (Kraut 2001). Similarly, in order to witness an effective and significant improvement in teachers’ practices in general and those related to the use of LMSs in particular, they should first understand, reflect and be aware of their own practices.

2.4.1 Definitions

Self-awareness refers to the ability of looking inside ourselves to get a clear snapshot of our thoughts, beliefs, emotions, motivations and overall personality. Developing self-awareness is more challenging than one might think. With this heightened awareness, it is easier to interpret one’s thoughts and emotions and to determine what one’s true feelings and motivations are (Duval et al. 1972). According to (Morin 2011), the most important distinction to highlight is that people can perceive and process environmental stimuli (e.g. a color, some food) without consciously knowing that they are doing so. However, they become self-aware when they reflect on the experience of perceiving and processing such stimuli (e.g. I am seeing a blue object, I ate food and it tasted good). (Duval et al. 1972) began the empirical study of self-focused attention. By exposing participants to self-focusing stimuli such as mirrors, cameras, an audience, and recordings of one’s voice, they showed that a state of self-awareness could be experimentally induced and reliably

produce heightened self-awareness.

Self-reflection and self-awareness are not very different and are closely related to each other. Thus, self-reflection involves a combination of introspection and willingness to learn about oneself in order to help achieve self-awareness. In other words, self-reflection encourages and develops self-awareness. (Morin 2011) described self-reflection as “a genuine curiosity about the self, where the person is intrigued and interested in learning more about his or her emotions, values, thought processes, attitudes, etc. This type of introspection mostly leads to positive consequences associated with good mental health”. Hence, being reflective and self-aware allows to identify and recognize areas that need development and how to improve them (Van Seggelen–Damen et al. 2020).

The induction of self-awareness with self-reflection stimuli leads to self-evaluation. The latter enables individuals to compare any salient aspect of themselves with an ideal representation of them. Self-criticism is then likely to occur, leading to either changing the target self-aspect or changing the ideal itself (Morin 2011). The figure 2.1 summarizes the relationship between the three concepts self-reflection, self-awareness and self-evaluation.

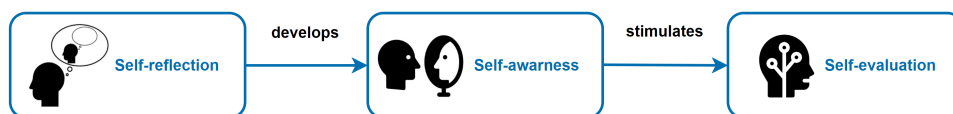


Figure 2.1 – Relationship between self-reflection, self-awareness and self-evaluation.

2.4.2 Teachers’ self-reflection

Some researchers have been interested in studying teachers’ self-reflection (Sammaknejad et al. 2016; Hollingsworth et al. 2017; McCoy et al. 2021). For example, (Hollingsworth et al. 2017) used videos to promote teacher learning, they therefore engaged in a study of a feedback approach to provide teachers with feedback on their practice as a mean of stimulating teachers’ self-reflection. The results showed that using videos for observation and analysis of practice facilitated teacher self-reflection and both supported and triggered teacher learning. (McCoy et al. 2021) examined the potential of digital video to support pre-service teachers in their self-reflective development. The analysis yielded strong evidence regarding the usefulness of digital video footage for supporting teachers’ weekly self-reflection and the development of their self-reflective practices. These studies

show the importance of feedback and the use of videos to improve teacher self-reflection. Thus, they can also be leveraged to improve teacher self-reflection when using LMSs especially feedback as the use of videos will not be interesting when using IT platforms (all the teacher's actions are done on the LMS).

2.4.3 Teachers' self-awareness

From the perspective of teachers, many researchers have studied teacher awareness in different contexts (Knowles et al. 2018; Sipman et al. 2021; Alea et al. 2020; Farrell 2013). For instance, (Farrell 2013) suggested promoting reflective practice for teachers through journal writing. They conducted an experiment with a college teacher in Canada over a two-year period. Findings showed that the teacher focused on writing about her self-awareness as a teacher and that frequent journal writing led to constructive behavioral changes inside and outside the classroom. Furthermore, (Alea et al. 2020) examined teachers' awareness of the COVID-19 pandemic and how they felt about the readiness of their schools, and their response to the challenges of distance learning. They also aimed to improve understanding of students with behavioral and emotional difficulties. These studies confirm that awareness allows teachers to self-identify positive and negative aspects of their teaching, leading to beneficial changes in their behavior.

2.4.4 Teachers' self-evaluation

Academics have a responsibility to continually monitor the effectiveness of their teaching. Regardless of the type of assessment used, the main determinant of the value of the information is the teacher (Taylor 1994). In this perspective, (Eisenring et al. 2019) attempted to analyze the English teacher's discourse through the use of Self-Evaluation of Teacher Talk (SETT). The latter is one of the tools often used as a reference to analyze classroom interaction. SETT allows the teacher to find out exactly what type of verbal interaction they are using and to what extent they are using it. The results of the interaction analysis are considered beneficial to the teacher, as they can develop their effectiveness in classroom discourse. Furthermore, based on the European Framework for the Digital Competence of Educators (DigCompEdu¹), (Ghomi et al. 2019) developed a self-assessment tool to measure the digital competence of teachers. The tool contains 22 items that represent the competencies listed in the framework. Within each item, there

1. https://joint-research-centre.ec.europa.eu/digcompedu_en

is a statement describing the core competency in concrete, practical terms, and 5 possible responses, cumulatively structured and mapped into proficiency levels. The teacher is requested to select the response that best reflects their practice. Findings show that teachers experienced in using technology in the classroom have significantly higher scores, which further validates the instrument.

Overall, if we can provide teachers with tools that allow them to reflect and become aware of their mastery of the LMS, we believe that they will be able to objectively evaluate themselves. The actions they conduct to improve their practices will be more accurate and efficient. Thus, this awareness and self-evaluation are very important to encourage teachers to use LMSs. However, they are not enough on their own to help teachers better master technology, they also need assistance in this learning process. At this point, it is important to consider how teachers are being supported in mastering LMSs and how it can be improved.

2.5 Teachers' support

An existing approach to support teachers in their teaching practices and their use of LMSs is through professional development programs. According to (Baran et al. 2014), the quality of online programs in higher education is strongly correlated with how well professional development approaches meet the needs of online teachers. (Bragg et al. 2021) defined online professional development as “structured, formal professional learning that is provided entirely online, resulting in changes to teacher knowledge, behaviour and practices”.

Similarly, (Baran et al. 2014) have hypothesized that successful online teaching requires support in several components at three levels as shown in figure 2.2: teaching, community and organization. Support at the teaching level consists of developing opportunities for teachers: workshops, training programs, or individual assistance. Community level support is based on the creation of learning groups: peer support programs (observation and peer feedback) and mentoring programs. Organizational level support aims at motivating and encouraging teachers to engage in online teaching: reward system.

According to (Frank 2003), the process of technology integration is evolutionary, and teachers' beliefs, pedagogy, and technology skills are slowly building on each other and co-evolving as technology is introduced and assimilated. Many common barriers to technology integration have been found to be overcome through mentoring. For example, (Polselli



Figure 2.2 – Professional development framework for online teaching (Baran et al. 2014).

2002) conducted a study on technology integration where mentors assisted teachers with online training. Results showed that 139 teachers who received mentoring support noted improvements in technology comfort levels, self-perceived skills, and the number of technological tools they use. Moreover, (Kopcha 2010) proposed a system-based mentoring model of technology integration. It outlines the ways a mentor can mediate the interplay of multiple barriers (time, beliefs, access, professional development, culture) on teachers learning to integrate technology and suggests a number of strategies for integrating technology, such as establishing a culture of technology integration, modeling technology use, and creating teacher leaders.

All these approaches are very interesting to help teachers with their practices. However, they have been criticized for placing too much demand on school resources such as time, money, and teacher support (Kopcha 2010). Yet, professional development approaches don't necessarily require an increased use of resources: the use of TELs and analytics can provide a simple way to do this. For example, leveraging recommendations and automatic feedback promotes peer support.

2.6 Synthesis

In this chapter, we first explored factors affecting the usability and acceptance of technology by teachers. Regarding the usability of LMSs, the literature is much more turned towards assessing usability with regard to students. However, teachers are key

actors in this type of platform and improving their usability can improve the quality of the teaching and learning process. On the other hand, several criteria affecting teacher acceptance and usability of LMS have been identified in the literature. The ones that come up frequently are:

- Ease of use
- Technological complexity/ functionalities
- Accessibility
- Satisfaction
- Subjective norm
- Teachers' self-efficacy

The first four criteria are related to the complexity of the LMS and its effect on the teacher, while the last two are considered social factors and thus do not depend on the platform. The subjective norm refers to the influence of others on the teacher's behavior and the self-efficacy is a personal criterion that does not depend on the LMS but only on the teacher's performance. We believe that it is possible to improve teachers' mastery of the LMS without changing the LMS. This can be done by taking advantage of the last two criteria, which allow for a better support and assistance to teachers in their LMS use, and thus positively impacting the first four criteria. In other words, if a teacher has the knowledge and skills to better meet their pedagogical needs on an LMS, they will be more comfortable with the features and be more confident in using an LMS platform as a teaching mechanism.

More specifically, teachers' beliefs and knowledge have proven to have a positive or negative impact on the barriers teachers face (Hew et al. 2007). For this reason, researchers began to study teacher's self-reflection, self-awareness, and self-evaluation. Those aim to help teachers better understand their own practices and thus improve them. Nevertheless, existing works in this area have not explored those concepts as a mean to enhance teachers' digital practices in LMSs. These psychological tools have proven their ability to change and improve people's practices. On the other hand, since many teachers are not able to accept the technology, we believe that their exploitation can help to engage them in a learning process of LMSs. Therefore, we intend to explore self-reflection and self-evaluation in the context of LMS use in order to determine their impact on teachers' behavior.

Teachers also need support and assistance to improve their practices in LMSs. To this end, professional development approaches have emerged providing strategies and

models for technology integration but costing institutions a lot of resources. However, there are further ways to leverage these approaches and strategies through the use of TEL and analytics. In particular, with the increasing adoption of LMSs, the field of analytics is becoming an important factor in the evolution of education. Therefore, the following chapter explains how analytics can be leveraged to support teachers and enhance professional development approaches.

LEARNING AND TEACHING ANALYTICS

Given the widespread availability of user-generated data in the various e-learning tools, particularly learning management systems, instructional processes can be further improved by extracting, processing and generating insights from various forms of analytics. In education, data-driven decision-making has become a common practice. Several institutions are mining various data and analytics in order to ensure a data-driven approach to all decisions that affect teaching and learning (Mandinach 2012). In this context, teaching and learning analytics (TA, LA) have emerged to also enhance the use of Technology Enhanced Learning itself.

This chapter provides an overview of learning and teaching analytics by considering their definitions, applications and methodologies. A summary of the similarities and differences completes this chapter.

3.1 Learning Analytics

3.1.1 History and definitions

Over the past decade, there has been expanding literature suggesting several types of analytics to support learning and improve educational outcomes and processes. Data mining in higher education gained momentum around 1995, following the advent of the Internet when greater interest in “educational data mining” emerged around 2004 (Winters 2006).

The first form of business intelligence introduced into the education sector is Academic Analytics (AA). These largely relate to the use of data-driven decision-making practices for operational purposes at either the university or college level, but can also extend to teaching and learning issues (Baepler et al. 2010). In other words, they mainly focus on data about the performance of academic programs to inform managers.

Thereafter, learning analytics (LA) emerged as a second branch of analytics, and it is

one of the fastest growing research areas related to the use of analytics in the educational context. While the field of learning analytics may seem recent (the first Learning Analytics and Knowledge (LAK) conference was held in 2011), they have their origins in older fields such as data mining or human-computer interaction (HCI). (Siemens et al. 2011) proposed the following definition of LA and it is the most used as of now: “measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimising learning and the environments in which it occurs”. They therefore relate to the collection and exploitation of traces left by learners to enhance the learning process.

However, a distinction can be made between academic analytics, data mining and learning analytics. Academic analytics (AA) are commonly viewed as hypothesis-driven (Baepler et al. 2010), applying a particular data set to solve a specific academic problem. More precisely, institutional management objectives and political strategies are linked to AA, such as supporting ethnic minority representation, increasing the organization’s productivity, etc. In contrast, LA provides algorithms to support cognitive goals in order to improve learners’ outcomes, enhance their engagement and optimize their learning experiences (Labarthe et al. 2016). On the other hand, data mining is considered more as a vast field to uncover all sorts of insensitive information and present useful insights that can, appropriately, be exploited by LA and AA.

3.1.2 Applications

A large amount of research has been conducted on LA to identify student behaviors, academic performance, achievement, and other related learning issues (Mwalumbwe et al. 2017; Dawson 2010; Clow 2013; Nguyen et al. 2021; Chatti et al. 2012). (Clow 2013) grouped the different applications of LA into 5 categories, as summarized in the figure 3.1: predictive modelling, social network, usage tracking, content analysis and semantic analysis as well as recommendation systems.

Predictive modelling

Several research studies have focused on predicting academic performance, analyzing student behavior in the learning environment, or examining the time each student spends on finding solutions to a problem in interactive classroom activities (Clow 2013). In a similar context, (Mwalumbwe et al. 2017) analyzed data from Mbeya University of Science

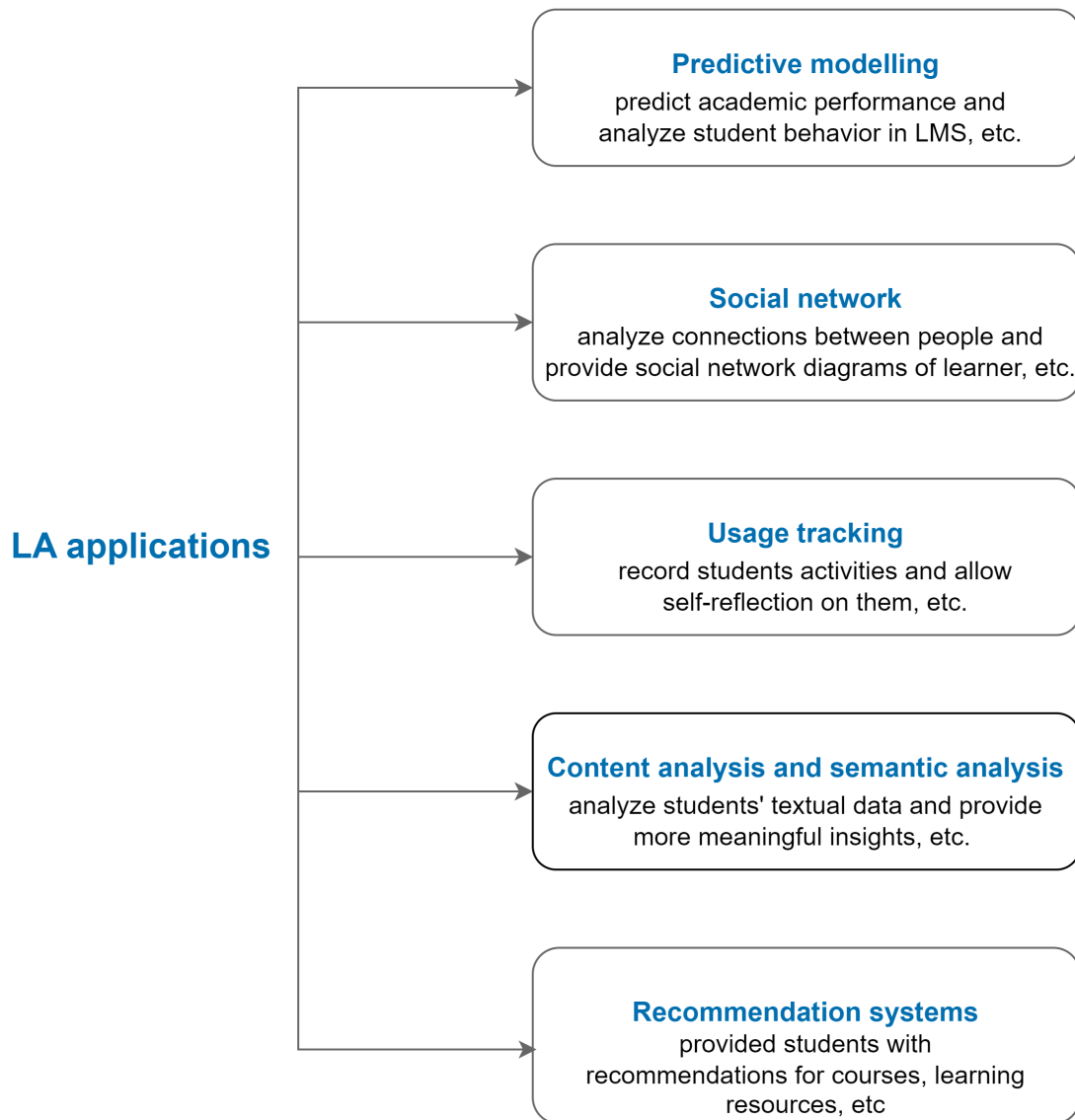


Figure 3.1 – LA applications.

LMS to investigate the relationship between student use of the LMS and their level of academic achievement. To do this, they applied a linear regression analysis using several variables such as the number of time users logged into the LMS, time spent within the system, the number of downloads, discussions, and dialogues between students, among others. Results showed that the number of discussions and interactions between students in the LMS, in combination with the number of assignments that a student solved, increased their academic performance level. However, the amount of time the student spent in the system and the number of logins and logouts had no meaningful impact on the student's success.

Social network

Social network analysis (SNA) has been exploited by several works to analyze the connections between people in a social context (Clow 2013). As part of e-learning, SNAPP (Social Networks Adapting Pedagogical Practice) was developed by (Dawson 2010). It allows teachers to track learner activity in the forums of learning management systems (LMS) or virtual learning environments (VLE) over time, providing a social network diagram where the individual learners are indicated by a red circle and the links between them are displayed as lines. SNAPP helps teachers to identify:

- Learners being completely disconnected either in or out of the network.
- Pattern of interaction in the forum (teacher-centered, peer interaction ...).
- Self-contained groups that interact with each other but not with those beyond the group.

Usage tracking

LMS, VLE, or any computer-based application allow the capture of student usage over time, and this can be used as a data source on student activity. For example, (Santos et al. 2012) developed a dashboard for students that allows self-reflection on activities and facilitates comparison with peers. Authors focused their work on a course in which students have to develop software and proceed through the different phases of its development process, such as design, programming and reporting. Afterwards, they used time-tracking software to record students activities on the different tools used (LibreOffice, Eclipse IDE, and Mozilla Firefox). The visualizations enabled students to determine the amount of time they spent on emailing, writing code, or searching for things compared to their peers.

Content analysis and semantic analysis

Nowadays, advances in data science, in particular in areas such as natural language processing and latent semantic analysis, have promoted textual data analysis. The latter is not limited to simple frequency counts, but can provide richer insights. In this perspective, the University of Technology of Sydney has developed and piloted the AcaWriter tool. It is a software program that helps students to develop their academic and reflective writing by providing them with automatic feedback. AcaWriter uses a natural language processing (NLP) parser, which can identify features of a learner's writing such as key concepts, people and places, and the degree to which the learner is acquiring scholarly knowledge (Shibani et al. 2019).

Recommendation systems

Research on recommender systems (RS) has expanded enormously. Such systems include all those capable of providing recommendations adapted to users' tastes, needs or means. In the context of LA, there are several works that have provided students with recommendations for courses, learning resources, etc. For example, (Nguyen et al. 2021) have developed a course recommendation system that selects appropriate courses for each student who is majoring in the following semesters based on their current academic performance.

3.1.3 Methodologies

To fully benefit from the advantages of learning analytics, there are several methods that allow for a better application of them (Leitner et al. 2017; Chatti et al. 2012), yet they are generally very similar. For example, (Leitner et al. 2017) introduced the LA life cycle presented in Figure 3.3. The cycle consists of four main stages:

1. A learning environment, which allows to collect data stored in MOOC, LMS or any other e-learning system.
2. Big data, represented by traces left by learners.
3. Analytics, which consist of the quantitative and qualitative methods used to discover hidden patterns inside of educational datasets.
4. An act, or the considered action as prediction, intervention, recommendation, personalization and reflection.

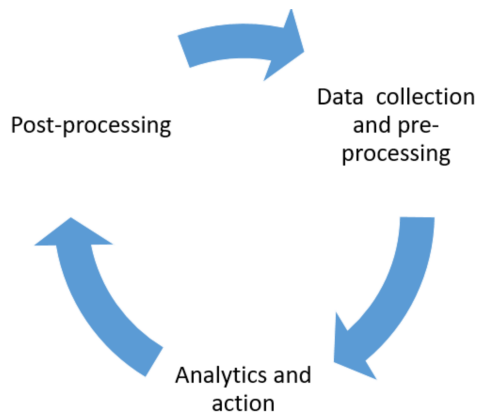


Figure 3.2 – Learning Analytics lifecycle (Chatti et al. 2012).

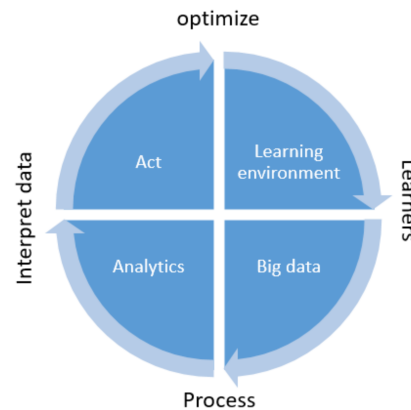


Figure 3.3 – Learning Analytics Process (Leitner et al. 2017).

Moreover, (Chatti et al. 2012) proposed a LA process (figure 3.2) that starts with a data collection and preprocessing phase to capture and prepare educational data, then passes through an analysis and action phase in which different LA techniques can be applied to discover hidden patterns. The latter involves not only analysis and visualization of information, but also actions on that information. The last phase is post-processing where the analysis can be improved by refining the data set, identifying new indicators/metrics or choosing a new analysis method, etc.

3.2 Teaching analytics

3.2.1 Definitions

Having explored LA, it is important to state that another field has recently emerged. Teaching analytics have been introduced to help complement and compensate for various types of analytics associated with the teacher and teaching practice. Two major definitions of Teaching Analytics can be found in the literature: (i) certain studies present TA as an approach to help teachers analyze and improve their instructional designs, including the analysis of how they deliver their lessons (Prieto et al. 2016; Ku et al. 2018). However, (ii) other studies consider TA as the ability to apply analytical methods to improve teachers' awareness of students' activities for appropriate intervention (Okoye et al. 2021; Ndukwe 2021). Nevertheless, the primary outcome of TA is to assist educational researchers in developing better strategies for supporting teachers' skills and knowledge.

3.2.2 Applications

The literature on TA can also be classified into several categories according to different criteria. In this respect, we looked for studies that focused on teachers, either by manipulating their data or by providing them with tools to improve their teaching. We found 18 studies that specifically focused on TA and summarized them in table 3.1. This enables us to propose a categorization of TA studies by objective, resulting in six groups and summarized in figure 3.4.

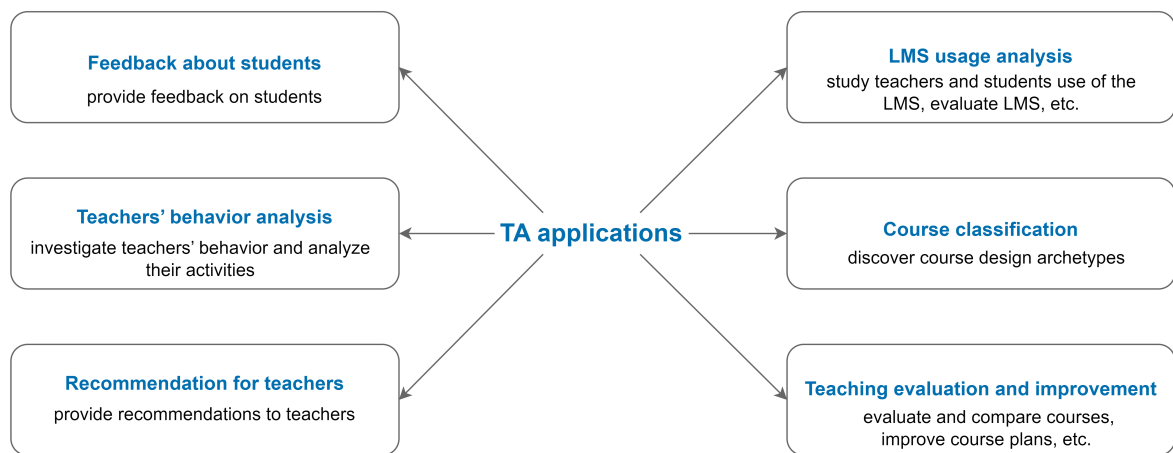


Figure 3.4 – TA applications.

Objective	Reference	Teaching method	Type of data used	Analysis method
LMS usage analysis	Rhode et al. 2017	LMS (Blackboard)	teachers' and students' data	statistical analysis
	Park et al. 2017	LMS (Moodle)	teachers' and students' data	statistical analysis
	Il-Hyun et al. 2017	LMS (Moodle)	teachers' and students' data	clustering analysis
Course classification	Whitmer et al. 2016	LMS (Blackboard)	students' data	clustering analysis
	Park et al. 2016	LMS (Moodle)	teachers' and students' data	clustering analysis

Teaching evaluation and improvement	Valsamidis et al. 2012	LMS (Moodle)	students' data	clustering analysis
	Regueras et al. 2019	LMS (Moodle)	teachers' and students' data	clustering analysis
	Iwasaki et al. 2011	LMS	teachers' data	qualitative analysis
Feedback about students	Barmaki et al. 2015	face-to-face	multimodal data of students	visualisation
	van Leeuwen et al. 2019	computer-supported collaborative learning	students' data	dashboard
	Pantazos et al. 2016	face-to-face	students' data	dashboard
Teachers' behavior analysis	Burton et al. 2011	hybrid learning systems	teachers' data	clustering analysis
	Albó et al. 2019	EdCrumble	teachers' data	visualisation
	Prieto et al. 2016	face-to-face	multimodal data of teachers	machine learning techniques
	Suehiro et al. 2017	e-book	teachers' and students' data	time-series analysis
Recommendation for teachers	Fazeli et al. 2012	all	teachers' data	recommender system
	Miranda et al. 2012	social web tools	teachers' data	recommender system
	Gallego et al. 2013	e-learning tool	teachers' data	recommender system

Table 3.1: Summary of TA studies by teaching method, data type and analysis method.

LMS usage analysis

Many researchers have studied teacher and student behavior in order to investigate LMS usage (Rhode et al. 2017; Park et al. 2017; Il-Hyun et al. 2017). In this context, (Rhode et al. 2017) used log files and database queries to examine how LMS tools were implemented in courses and used over time. They adopted a binary approach to determine

if a tool (announcement, items, grades, folders, files, assignments, web links, plagiarism, discussion boards, tests) was used in a course or not. The results identified the most frequently used features and how their usage had changed over time. On the other hand, the work of (Park et al. 2017) aimed to evaluate the usage patterns of an LMS. For this purpose, a large dataset was analyzed. It included three general indicators (login frequency, members, average login frequency) and ten activity indicators (announcement, links, lecture note, resource, questions and answers, discussion, quiz, wiki, assignment, group work). The results of this study have also identified the most used features in the LMS. Furthermore, (Il-Hyun et al. 2017) applied three different clustering techniques to 2639 higher education courses with the aim of helping in understanding the pedagogical approach of the teachers and the level of integration of the LMS used. As a result, they identified four clusters, each with different LMS usage strategies (forum-based, quiz-based, wiki-based and resource-based).

Course classification

Several other studies have been conducted to classify teachers' courses (Whitmer et al. 2016; Park et al. 2016). For example, (Whitmer et al. 2016) aimed to discover course design archetypes across multiple institutions. To this end, they calculated time spent using each tool (assessment, announcement, grade book, assignment, content, discussion board). Then, they performed a clustering analysis (Kmeans) and identified five groups: (1) Supplementary (heavy content, low interaction), (2) complementary (one-way communication via content, announcements, and gradebook), (3) social (high peer interaction via discussion forum), (4) evaluative (heavy use of assessments), and (5) holistic (high LMS activity with balanced use of assessments, content, and discussions). Similarly, (Park et al. 2016) used a data-driven approach with the LCA method of clustering to classify blended learning courses on the basis of multiple features (announcement, links, lecture notes, resources, questions and answers, forum discussion, quiz, wiki, assignment, group work). Four unique course subtypes were identified: (1) Inactive or immature (low levels of use in online learning activity), (2) Communication or collaboration (high use of Q&A and group work), (3) Delivery or discussion (high use of course notes, links and discussion forum) and (4) Sharing or submission (use of resources and submission of assignments).

Teaching evaluation and improvement

The analysis of data can also provide a way to evaluate and compare the courses of teachers. In this perspective, (Valsamidis et al. 2012) used Markov Clustering and K-means algorithms to analyze LMS courses and student activity, then computed metrics based on the number of sessions and page views per student. The results indicated that the proposed metrics can provide a preliminary ranking of courses which can be used to evaluate teachers' courses. Moreover, (Regueras et al. 2019) proposed a method to automatically certify teachers' competencies from LMS data to help universities make strategic decisions. They used variables related to the teacher (resources, forum post, gradebook, feedbacks, calendar, quizzes, grade feedbacks, grade items, etc.) and others associated with the students (resource consultation, forum post and views, assignment submission, quiz submission, etc.). Three clustering methods were applied, and they were able to identify 6 types of courses (non active, submission, deposit, communicative, evaluative, balance) that were used to certify teachers.

On the other hand, some researchers were interested in teaching improvement and supporting teachers (Iwasaki et al. 2011). They proposed appropriate methods to accompany and help teachers to develop their course plans. Thus, researchers analyzed the relationship between the use of an LMS and the epistemology of teachers as well as the characteristics of the courses. The data used were collected through a questionnaire and interviews with teachers. Regarding epistemology, they asked teachers to rate whether their course was student-centered, their emphasis on the exchange of opinions among students, and how they incorporate student actions. For LMS use, they asked how and why teachers use the LMS, the most used LMS features, its effectiveness, and the problems they encountered while using it, etc. After an in-depth analysis, the authors were able to identify three categories of courses and propose methods for coaching teachers for each type of course: (1) Knowledge Construction, (2) Knowledge Transmission, and (3) Blended. Teachers of knowledge construction courses are interested in fostering opportunities for students to think for themselves, rather than simply transmitting knowledge to students. Whereas teachers of knowledge transmission courses believe that students need to acquire basic knowledge to develop the skills required by society. Teachers of blended courses value the importance of independent learning, promote opportunities for independent thinking, and encourage active learning.

Feedback about students

Various studies have leveraged TA to provide feedback on students as a mean of helping teachers to better organize and manage their courses, and generally using the Teaching analytics dashboard or TAD (Ndukwe 2021; Barmaki et al. 2015; Pantazos et al. 2016). The latter is a category of dashboard for teachers that holds a unique role and value. It could allow teachers to access student learning in almost real-time and scalable manner, therefore, allowing teachers to improve their self-awareness by monitoring and observing student activities. It also tracks teachers' personal activities, as well as students' feedback on their teaching practice (Ndukwe 2021).

In this context, (Barmaki et al. 2015) aimed to capture automatic real-time feedback based on speaker posture to help teachers to perform classroom management and content delivery skills. They used different types of multimodal data, including talk-time and nonverbal behaviors of the virtual students. A visual indication was provided to the teacher whenever the participant exhibited a closed or defensive posture. As part of computer-supported collaborative learning (CSCL), (van Leeuwen et al. 2019) developed a teacher dashboard prototype that provides information regarding several aspects of student collaborators' activities (e.g., the number of attempts on a task and the amount of discussions within a group), thus affording insights into the cognitive and social aspects of collaboration. On the other hand, (Pantazos et al. 2016) designed a TAD that visualizes student repertory grid¹ exercise data. The purpose was to help teachers to investigate and compare students' personal constructs and item ratings for given topics of study. In addition, this dashboard facilitates formative assessment feedback to students and allows for improvements in current teaching practices. It was evaluated by 6 teachers who indicated that such dashboards were lacking in their regular practice and would recommend their use in a formal business educational setting.

Teachers' behavior analysis

Many studies have been conducted to investigate teachers' behavior (Burton et al. 2011; Albó et al. 2019). For instance, based on a reference framework built by Charlier, Deschryver and Peraya, (Burton et al. 2011) have developed a survey of 24 questions for 174 teachers in more than 22 higher education institutions and universities in Europe. The

1. The repertory grid technique (RGT or RepGrid) is a method for obtaining personal constructs, i.e., what people think about a given topic. It is essentially a matrix consisting of a set of provided or obtained "elements" and a set of provided or obtained "constructs" (Christie et al. 1997)

collected data from teachers allowed the researchers to carry out cluster and correspondence analysis to finally propose an organization of 6 types of hybrid learning systems ranging from the least developed to the most developed and describing the behavior of teachers in each. In contrast, (Albó et al. 2019) analyzed the behavior of teachers during the instructional design phase of their courses, using the edCrumble system² to compare the use of the design tool both with and without the visualization of the learning activities that are being created. To this end, they collected the actions log of the instructors while they were interacting with the system including total actions, deleted activities and the time spent in the system. The purpose of their study was to assist teachers in making design decisions based on these visualizations. Therefore, they provide important indicators for studying the behavior of teachers. However, they designed these indicators in a bottom-up approach, starting from the tool they use and the data it generates to the definition of features and then a framework of decision making. Consequently, this approach has some limitations in terms of reusability due to the absence of a model or a method allowing its exploitation in other technological contexts.

Some researchers have also attempted to analyze teaching activities in classroom settings (Prieto et al. 2016; Suehiro et al. 2017). Given this context, (Prieto et al. 2016) automatically extracted teaching actions during face-to-face classrooms (explanation, monitoring, testing, etc.). They used data collected from multiple wearable sensors (including accelerometers, EEG and eye-trackers) and explored machine learning techniques to characterize what teachers really do all along their courses. This study allowed to automatically detect the teacher's activity (explanation, monitoring, questioning...), and to make a distinction between the different scopes of teacher interactions (one-to-one, with a small group or with the whole class). Moreover, (Suehiro et al. 2017) used a novel approach to employ teaching analytics in face-to-face courses in order to extract teaching activity efficiently and accurately. To do this, they collected data through the use of e-book logs without optional devices or tools. Thus, they focused on logs involving slides that a teacher shows in class as well as those logs showing what students are reading. The findings demonstrate that their analysis was successful in accurately extracting teaching activities.

2. EdCrumble is a scripting system for planning hybrid courses. It allows instructors to design activities with educational technologies, explore and reuse others' courses and activities within a community of educators, etc.

Recommendation for teachers

Recommender systems (RSs) include all systems capable of providing recommendations adapted to users' tastes, needs or means. In the context of education, RS has become more and more popular with most of them targeting learners. The literature lacks of works that proposes RS for teachers (Dhahri et al. 2021). Among the existing ones, there is the work of (Fazeli et al. 2012) who have proposed a social recommender system that helps young teachers to find peers who are best positioned to solve their problems. Furthermore, (Miranda et al. 2012) have developed a system that recommends online comments elaborated by teachers (suggestions from teachers to their peers) about their experience in conducting educational activities in an online educational community called Kelluwen. In Kelluwen, teachers build, use and share collaborative instructional designs whose educational activities are based on social web tools. (Gallego et al. 2013) proposed a model to generate proactive and contextual recommendations on resources during the process of creating a new learning object that a teacher conducts using an e-learning tool. The latter also highlights the importance of recommending LMS features to teachers in order to improve their practices.

The studies presented in this section constitute the majority of those we can find in the literature. Although there is a diversity of objectives, they are not sufficiently explored. Compared to LA, TA are still under-explored given their importance. Moreover, these existing studies include in most cases students in their investigations, which renders their findings partial. On the other hand, if we focus on the use of LMSs, we notice that existing works analyze the use of these platforms and classify courses. However, it becomes evident that the few TA studies analyzing LMS rarely use their findings to support teachers (Fazeli et al. 2012; Miranda et al. 2012). For example, self-evaluation and self-reflection are important ways to motivate teachers to learn and enrich their practices within the LMS, as discussed in the section 2.4.4. However, such exploitation has not been explored so far in the context of TA.

3.2.3 Methodologies

Regarding TA, it seems that TOM is the only method proposed to explore them. TOM or Teaching Outcomes Model is a lifecycle designed by (Ndukwe 2021) and presented in the figure 3.5. It aims to help teachers regularly identify, match and adjust their teaching practice and learning design. It starts with a stage where data is extracted and collected.

In the second stage, data analysis is performed to discover hidden patterns using different machine learning techniques. Then, in a third stage, the previous outcomes are provided through visualizations embedded by a Teaching Analytics Dashboard (TAD). Eventually, in the action phase, teachers implement specific measures to improve their pedagogical practices.

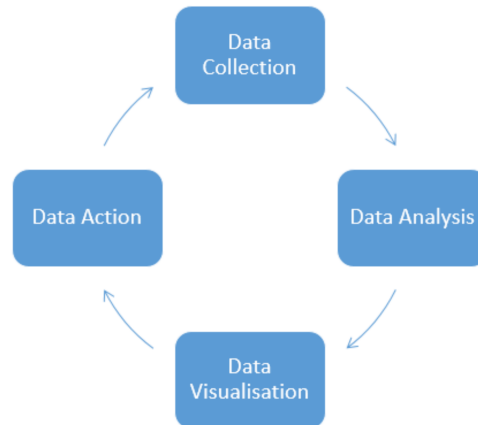


Figure 3.5 – TOM lifecycle (Ndukwe 2021).

These models and methods proposed for the exploitation of LA and TA are important and useful. However, we think that the inclusion of users and experts is lacking. Particularly for TA, we believe that explaining how to deal with teachers is crucial since it is generally more difficult to manipulate their data than students' data due to privacy issues.

3.2.4 Theoretical approaches

It is important to mention that some works have been carried out to achieve the same goals of TA (improving teaching, analyzing teachers' behavior, etc.) but without using data or analytics (Coomey et al. 2018; Sergis et al. 2017; Charlier et al. 2006). In this respect, some researchers have proposed theoretical approaches to facilitate the understanding of teaching practices especially in e-learning tools. For example, (Coomey et al. 2018) identified four main characteristics of e-learning (DISC) which are considered essential to good practice: Dialogue, Involvement, Support and Control. Thereafter, they proposed four paradigms according to variations in locus of control (teachers or students) and task specification (strictly specified or open) with a list of advices for each paradigm.

The first paradigm is named Active Induction where the activities are closed and managed by the tutor while the second one “Guided Exploration” concerns closed activities managed by students. The third paradigm is called Facilitated Investigation for open activities managed by the tutor and the last one, Self-Organized Learner relates to open activities managed by students. In addition to this study, the European Hy-Sup project proposed a typology of hybrid learning systems for which they analyzed specific effects on a certain number of teaching and learning variables (Burton et al. 2011). Their work was based on a reference framework built by Charlier, Deschryver and Peraya which offers five main dimensions to describe hybrid learning systems (Charlier et al. 2006): (1) Modalities of articulation of face-to-face and distant phases, which are characterized by the time allotted to each mode, their distribution, and the types of activities used by the teacher in each phase, (2) human support, referring to the work on the learning support by the teacher, (3) forms of media, which concern the processes of design, production and implementation of devices, a process in which the choice of the most suitable media occupies an important place, (4) mediation, defined as the process of transformation that the technical device produces on human behavior and (5) degree of openness which corresponds to the learner’s degree of freedom in learning situations. Finally, (Sergis et al. 2017) analyzed the current state-of-the-art in teaching and learning analytics research, using the concept of teacher inquiry as a core analytical framework, in an effort to provide a transparent overview of global insights and gaps. They subsequently proposed the concept of Teaching and Learning Analytics (TLA) as a synergy between Teaching Analytics and Learning Analytics in order to support the process of teacher inquiry. The latter is defined by (Avramides et al. 2015) as a set of actions in which “teachers identify questions for investigation in their practice and then design a process for collecting evidence about student learning that informs their subsequent educational designs”. This process aims at improving teaching practice by collecting feedback from students.

The different approaches presented here are interesting as they are based on expert studies. Since TA serves the same purpose, we think that combining them with theoretical approaches, i.e., involving experts in the process, may yield more robust and reliable results for teachers’ benefit.

3.3 Synthesis

This chapter discusses the most recent analytics in education: learning and teaching analytics. Although they are defined in a different way, they both share the same goal of analyzing educational data and improving the teaching and learning process. In particular, both serve as a pedagogical tool for assessment, improvement and decision-making. On the other hand, the target audience constitutes the main difference between learning and teaching analytics. The former is learner-centric whereas the latter is teacher-centric. However, TA includes in most cases students' data in order to achieve their goals related to teachers. Furthermore, TA are recent and relatively unexplored compared to LA whilst featuring great potential for improving on teaching methods and content delivery.

There remains a misperception between LA and TA that revolves around educational data used by them. The general impression tends to assume that TA is a subset of LA instead of a distinct field by itself sharing common educational data points with LA. Teaching analytics helps educators to improve the teaching and learning environment. Therefore, the direction of research on TA should be conducted from the educators' perspective instead of focusing solely on the learner's perspective to improve the educational process (Khuzairi et al. 2020).

Existing works on TA target various purposes: some studies attempt to categorize courses, to evaluate and improve teaching or to analyze the overall use of LMS, while others aim at providing teachers with feedback about students or recommendations. However, it appears that none of them have targeted the analysis of the teacher's behavior for its application on self-evaluation. On the other hand, these studies give proper insights to what is currently done on the LMS, and may be used to compare a teacher to another, but present common limits. Furthermore, the most frequent data that have been collected and analysed focus on students rather than on monitoring only teacher activities. These student-related data are difficult to compare since it is not the same population, nor the same number of students, etc. Moreover, they all lack validation from teachers or experts to better understand findings and make them more relevant and meaningful.

Some theoretical studies have been carried out to improve and analyze teaching on the basis of theories and experiences of educational specialists. By leveraging these approaches, TA can produce more insightful results. Therefore, given all these limitations, we consider that teaching analytics stand for **leveraging teachers' data to help them understand, analyze, and improve their teaching design within a user-centered**

approach. The choice of focusing only on teachers' data in the context of a user-centered approach is mainly made to gain teachers' trust and increase the chances of acceptance and adoption of TA results by them.

In the context of this thesis, we want to exploit teaching analytics in order to analyze teachers' behaviors and assist them in using learning management systems. The first chapter of the state of the art showed that LMSs are not used to their full potential and teachers still face problems in integrating their practices into their institutional LMSs. The second chapter provided some ways that might change this situation, including supporting teachers' self-reflection, self-awareness, and self-evaluation, as well as exploring the various methods of their professional development, that have not yet been implemented in order to improve the use of LMSs by teachers.

Hence, we aim, throughout the rest of this manuscript, to (i) provide teachers with tools to help them be more reflective, aware and able to evaluate their own use of the LMS, (ii) support them in the learning process in order to enrich their practices in the institutional LMS and finally (iii) offer teachers a support tool that can be easily used.

PART II

Towards a teaching analytics tool

METHODOLOGY

To address our research questions, it is essential to follow a well-defined methodology in order to effectively carry out the different phases of our research.

Since our purpose is to assist teachers in understanding and improving their practices on the institutional LMS, we have leveraged teaching analytics as they are intended for this goal. Therefore, we have identified the TOM model we reviewed in section 3.2.3. It aims to provide teachers with assistance on how to approach and reflect on teaching data. It therefore suggests 4 phases: data collection, data analysis, data visualization and data action. However, we have identified some limitations to this approach, in particular the lack of validation and users' implication.

In this chapter, we explain these limitations then we detail the TOM^{++} methodology that we propose as an extension to TOM.

4.1 TOM^{++}

TOM is an interesting model for analyzing teacher behavior, however it is limited to quantitative analysis which may yield inconclusive or partial findings without a qualitative study or expert validation. Furthermore, the visualization phase does not involve end-users to obtain their needs and preferences. Taking these limits into account may increase the possibility of these visualizations to be more accepted and adopted by teachers. Thus, we consider that the integration of users and experts (PEs) in our methodology is crucial for the achievement of our work. It can be reached by taking advantage of user-centered methods.

4.1.1 Integration of user-centered methods

To involve end-users in a research project, two types of user-oriented approaches are commonly followed: a user-centered approach or a participatory approach. They both al-

low to capture users' needs and thus develop, in an iterative way, a quality tool that meets their expectations (Dabbebi et al. 2019). The user-centered design practice incorporates careful consideration of users' needs, desires, and their limitations throughout the design process, which allows for the assessment of both effectiveness and relevance of the tool (Khaled 2021). For instance, (Dabbebi et al. 2019) employed this approach to ensure an explicit understanding of user needs and contexts in order to develop a dynamic learning dashboard generator. On the other hand, participatory approaches belong to the user-centered approaches, but they advocate the active involvement of users, which means performing all the steps of a project in a collaborative and shared way so that the product meets users' needs and is usable (Spinuzzi 2005). For example, (Dabbebi et al. 2019) have developed a method for participative design of learning dashboards, which is called PADLAD (Participatory Design Of Learning Analytics Dashboards). It interrogates and guides participants through different steps to achieve adaptive learning dashboards design for students and to evaluate their impact on learning. The online version of the design tool of this method is called e-PADDLE (PARTicipative Design of Dashboard for Learning in Education) developed by (Oliver-Queleennec et al. 2021).

In the context of our work, we aim at developing a tool for teachers that does not require teacher involvement in all the design phases. Therefore, we have opted for a non-participative user-centered approach. We explain how the latter can be integrated into TOM in the next section.

4.1.2 Enhanced TOM

In this work, we propose the TOM^{++} methodology. It extends the cycle proposed by (Ndukwe 2021) with two layers of validation represented by an orange color in the figure 4.1. The first layer consolidates the data analysis phase by conducting a qualitative study to involve teachers and/or experts. This allows to validate results of the quantitative studies and also to identify further patterns regarding teachers' practices and issues. Once the necessary number of iterations has been performed, final results should be more relevant, reliable and thus ready to be displayed.

The second layer is related to the data visualization phase. It aims to include teachers in the process of selecting visualizations and the different functionalities of the tool researchers are proposing (if any). It can be realized by collecting their needs and preferences. The outcomes of this phase provide teachers with solutions that are more in line with their expectations which increases the chances of these solutions to be appropriated

and used by them.

By involving teachers in the TA process, more specific and precise actions can be expected from them during the final phase (action phase) in order to improve their practices. Furthermore, teachers can provide researchers with more accurate feedback and suggestions to help them improving their solutions.

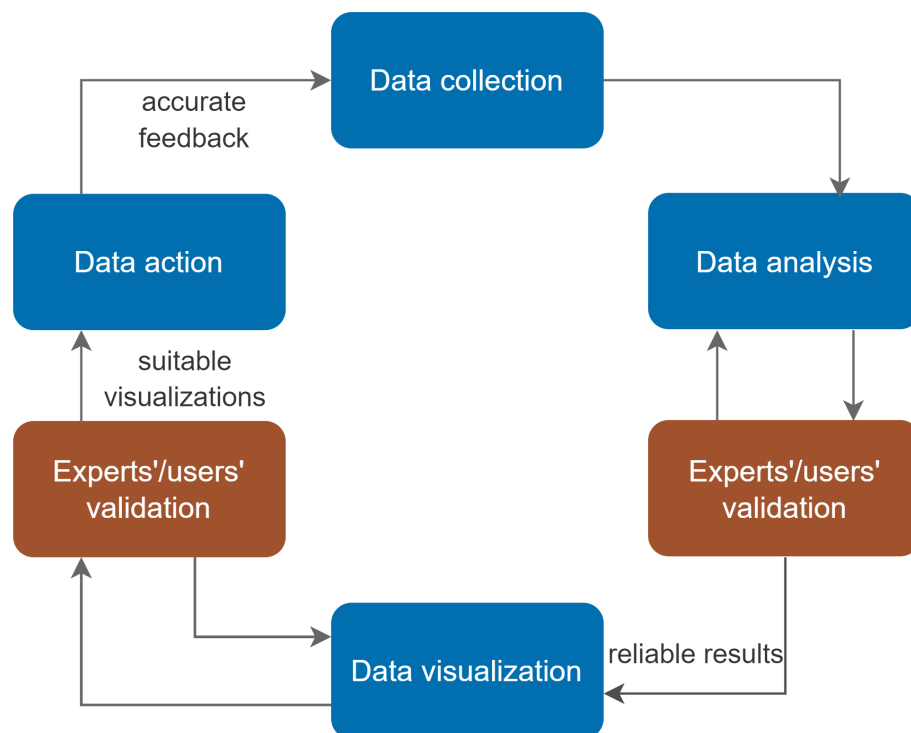


Figure 4.1 – *TOM++* methodology.

4.2 Data collection

The LMS of our university is a Moodle platform named Umtice. It is used as a techno-environment to support the teaching-learning process but mainly in face-to-face settings. Umtice has been widely used by most teachers (about 640 teachers and teacher-researchers) and students (about 12,000 students per year) for 15 years.

We recovered traces of teachers' activities from June 2016 to July 2018 and from October 2019 to October 2021 (an IT failure on the University's LMS caused the loss of

data between the two periods).

To facilitate the exploitation of Umtice data, an ETL (extract, transform and load) was set up to extract users' activities from the Moodle sql database as well as the university's directory (administrative data), transform them into xApi¹ format and finally store them in an ElasticSearch LRS (Learning Record Store). We chose to use the xApi convention because it provides a simple and lightweight way to store, retrieve and share user records across platforms. Following this format, each user action is represented as a standalone document that provides a view of the related course, activity (if any) and details of the user at the time of the action. The choice of ElasticSearch as an LRS was based on our need to search and analyze data. For this purpose, ElasticSearch is among the most convenient and commonly used LRS (Shah et al. 2018). It can search and index document files in various formats and it is able to achieve fast search responses as well.

On the other hand, we required some additional administrative data that were not extracted by the ETL: teachers' departments, their emails and their sites (as our university is spread over two distant sites). Therefore, we used the LDAP protocol to retrieve them from the university's directory. Accordingly, data used throughout this work combines those of ElasticSearch database and the university's directory as shown in figure 4.2.

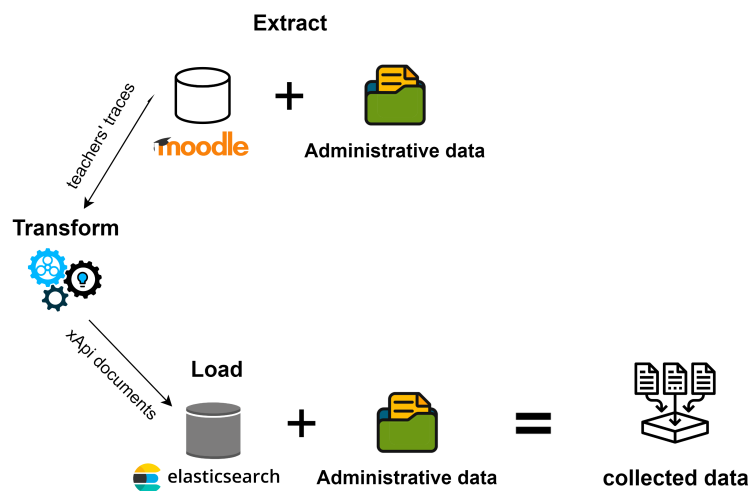


Figure 4.2 – Data collection.

1. <https://xapi.com/overview/>

4.3 Data analysis and its validation

In order to qualify teachers' use of the LMS, we applied a quantitatively driven mixed methodology (R. B. Johnson et al. 2007). We started by the quantitative analysis to deduce statistically different profiles of LMS use, based on LMS log data. We therefore performed a Principal Component Analysis (PCA) to detect groups of teachers or profiles of interest in a reduced set of variables.

Afterwards, we conducted semi-structured interviews (i.e. qualitative interviews) with pedagogical engineers to validate and enhance the results of the first analysis (validation by experts). In a set of open-ended questions prepared in advance to guide our interview, we collected information to improve the quantitative study. This qualitative method was chosen because we needed the interviewee to answer freely, express any specific point of view, and bring out potential new working hypotheses (Magaldi et al. 2020). We also chose to interview pedagogical engineers because teachers were not very available during that period (lockdown, that induced an overhead of work for teachers to adapt all their practices in remote settings). Moreover, PEs have good knowledge of teachers' practices and how they use the University's LMS.

In order to design a behavior model that can handle both present and future expected use of the LMS by teachers, we merged the results we obtained from the latest quantitative analysis and those we obtained from the interviews with PEs. Following this step, we proposed a behavioral model that describes in a comprehensive way teachers' practices on the institutional LMS.

Based on this model, we designed several TA metrics to support teachers' self-reflection and self-awareness. Furthermore, we proposed different recommender systems to help teachers improving their practices on the University's LMS.

The figure 4.3 summarizes the different steps of the data analysis and its validation.

4.4 Data visualization and its validation

In order to instrument the model and its indicators within an application that would be more easily accepted by teachers and PEs, we elaborated an online questionnaire for teachers, and we also scheduled interviews with directors of the Digital Resource Center (DRC) and pedagogical engineers (PEs) in order to get their needs and preferences.

After multiple iterations to develop the application, taking into account feedback from

teachers and PEs, we released the application named **iTeachApp**. The steps presented in figure 4.4 and detailed in chapter 7 allowed us to validate our visualizations and interfaces.

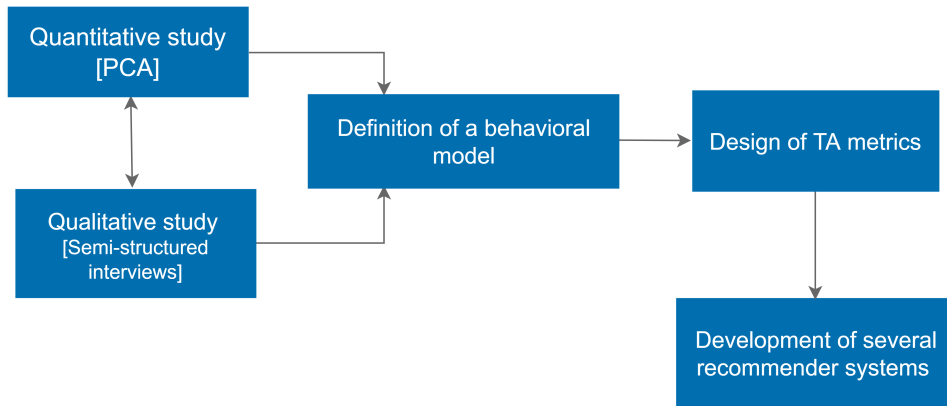


Figure 4.3 – Data analysis and its validation.

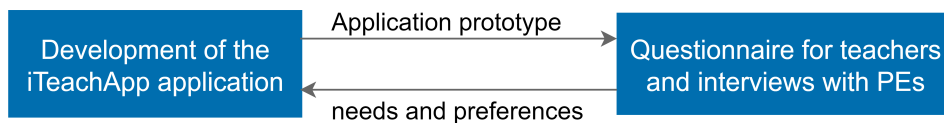


Figure 4.4 – Data visualization and its validation.

4.5 Data action

In this phase, we experimented iTeachApp at the scale of our university in order to study its usability and appropriation by teachers as well as PEs’ interest in it. To this end, we adopted the mixed approach (quantitative and qualitative) presented in figure 4.5. A first qualitative analysis process aimed at collecting participants’ feedback on the application through a usability questionnaire. A second process aimed at studying traces of iTeachApp in a quantitative approach to examine how teachers really used the application (more details in chapter 8). The results of this phase allowed us to identify areas of improvement regarding our proposals and application. On teachers’ side, it enabled them to reflect on their practices related to the LMS and possibly act to enrich them.

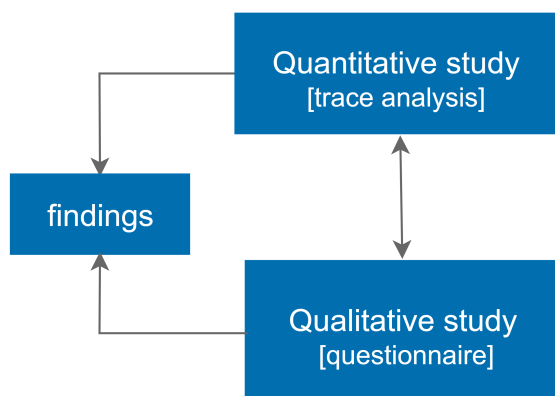


Figure 4.5 – Data action.

4.6 Synthesis

For the purpose of providing teachers with a support tool that helps them to self-evaluate and improve their practices on the university’s LMS, we have proposed the TOM^{++} methodology. It provides an additional layer of validation to the data analysis and visualization phases. A qualitative analysis is required to obtain more information from teachers and/or experts, which validates the quantitative analysis and provides more consistent and reliable results. Researchers should consider needs and expectations of teachers during the visualization phase, as this can increase their acceptability and usability of the proposed solution.

Throughout this thesis, we followed the TOM^{++} methodology which was an important foundation to answer our research questions. Each phase provided us with relevant findings to achieve our objectives. The following chapters explain each phase in detail and present the results we obtained.

TEACHERS' BEHAVIORAL MODEL

This chapter aims to expose the first part of the data analysis phase introduced in the previous chapter as shown in figure 5.1. Therefore, we focus here on the analysis of teachers' behavior on the institutional LMS through a mixed-driven approach. Its objective is to study how the LMS is truly used by teachers. Thus, we need to propose a model that describes this use in an intelligible and exhaustive way. For this purpose, we carried out a quantitative study using collected data (see section 4.2) and then a qualitative study by conducting semi-structured interviews with PEs from our University. Through the intersection of these studies, we designed a behavioral model of teachers that will be detailed in this chapter.

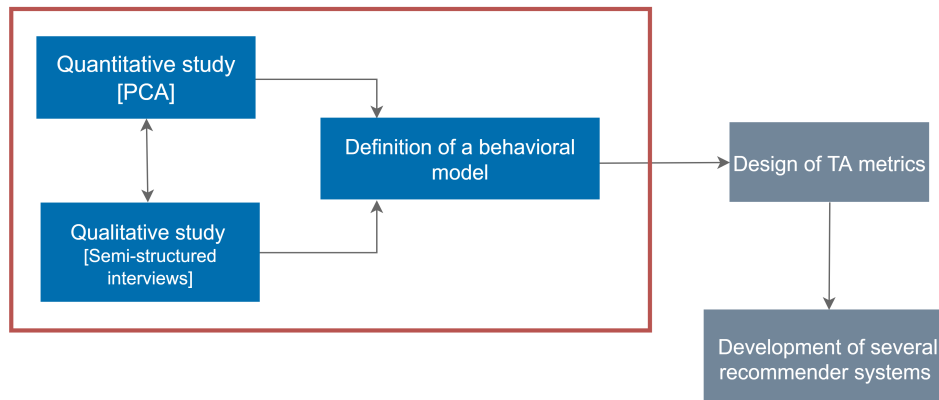


Figure 5.1 – Quantitatively driven mixed method.

5.1 Dataset creation

Figure 5.2 describes models of the ElasticSearch LRS created by the ETL (presented in the section 4.2). Each document is primarily defined by an event (action) related to a

user, a course, or an activity model (it can be related to all of these at the same time). The current ElasticSearch includes other models, but we only present here those used in our research work.

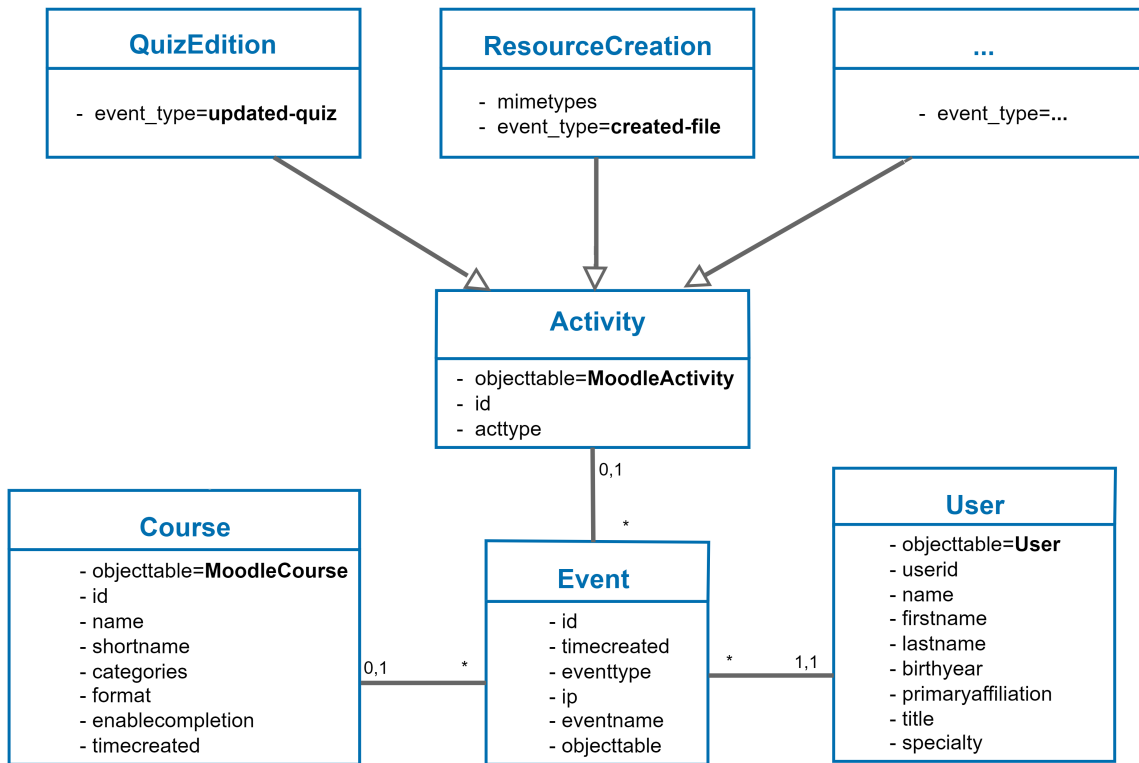


Figure 5.2 – ElasticSearch document models.

Each action of a user is modeled in an uniform way. An event is an autonomous document that represents an action, the user that initiated it with its administrative information, the course and the activity where the event took place (if any). In the ElasticSearch, each model includes an *objecttable* property that can be used to track the origin of the remaining attributes in the Moodle SQL database. The event model is characterized by an identifier, the time of the action creation, the IP address of the machine where the event was created, the original type of the event (*eventname*) and the event type defined during the transformation (*eventtype*). This event can be performed by a user who is described by an identifier, first and last name, year of birth, affiliation (e.g. teacher, staff, etc.), title (e.g. professor) and speciality (e.g. computer science, languages, etc.). The user's action can be on a course and/or an activity. The course model includes an identifier, its name,

a list of its categories, its format (topics, site, weekly¹, etc.), the creation time of the course and a Boolean property indicating if the completion is allowed or not. The latter is a traceability feature that allows the teacher to verify whether a student has completed the prior activities. Finally, the activity model which is also represented by an identifier and an activity type (*acttype*). The activity types that we were able to determine are presented in the table 5.1.

We have recorded several types of event (actions), we list them below with some examples of the related types (*eventtype*):

1. **Connection:** *logged-in, logged-out.*
2. **Creation:** *created-course, created-choice, created-forum-discussion.*
3. **Deletion:** *deleted-course, deleted-survey.*
4. **Update:** *updated-quiz, updated-assignment-submission*
5. **Manipulation:** *sent-chat-message, add-calendar-event, quiz-attempt, grade-student.*
6. **Visualization:** *viewed-game, viewed-assignment-feedback, viewed-forum.*

These events were not distinguished during the creation of features in order to keep the maximum information in the dataset. Due to the low use of the LMS, separating each type of event will result in variables that are likely to have low variance and thus be removed in the preprocessing phase required for PCA and clustering algorithms.

5.2 Quantitative study

In this section, we present the quantitative study that we performed to identify the different profiles of LMS use by teachers. It is important to mention that these results are derived from the second iteration after the qualitative study. The latter allowed us to add some variables and adjust the calculation of others.

Based on the LRS, 30 variables have been identified to analyse teachers' behavior with 974 teachers who did at least one action related to these features : *course_format* , *file*, *all_links*, *label*, *url*, *page*, *forum_discussion*, *folder*, *calendar*, *forum*, *grade*, *assignment*, *lesson*, *quiz* , *forum_post*, *wiki*, *chat*, *chat_message*, *img*, *via*, *glossary*, *choice*, *gallery*, *data*, *game*, *workshop*, *lti*, *attendance*, *survey*, *book*. These variables were defined by calculating the average number of manipulations per course made by the teacher on Umtime

1. https://docs.moodle.org/400/en/Course_formats

Table 5.1 – Description of Umtice's activities.

Activity type	Description
<i>Assignment</i>	it enables a teacher to communicate tasks, collect work and provide grades and feedback.
<i>Attendance</i>	it enables a teacher to take attendance during class and students to view their own attendance record.
<i>Chat</i>	it enables participants to have text-based, real-time synchronous discussions.
<i>Choice</i>	it enables a teacher to ask a single question and offer a selection of possible responses.
<i>Database</i>	it enables participants to create, maintain and search a collection of records defined by the teacher.
<i>External tool</i>	it enables students to interact with learning resources and activities on other web sites.
<i>Forum</i>	it enables participants to have asynchronous discussions i.e. discussions that take place over an extended period of time.
<i>Glossary</i>	it enables participants to create and maintain a list of definitions, like a dictionary, or to collect and organise resources or information.
<i>Journal</i>	it enables teachers to obtain students feedback about a specific topic.
<i>Lesson</i>	it enables a teacher to deliver content and/or practice activities in interesting and flexible ways.
<i>Calendar</i>	it allows to display site, course, group, user and category events in addition to assignment and quiz deadlines, chat times and other course events.
<i>Survey</i>	it provides a number of verified survey instruments that have been found useful in assessing and stimulating learning in online environments.
<i>Quiz</i>	it enables a teacher to create quizzes comprising questions of various types, including multiple choice, matching, short-answer and numerical.
<i>Via</i>	it allows participants to create synchronous meetings in a virtual classroom to share live using voice and video for: remote classes in real time, meetings, work-team meetings, tutoring, seminars, etc.
<i>Wiki</i>	it enables participants to add and edit a collection of web pages. A wiki can be collaborative, with everyone being able to edit it, or individual, where everyone has their own wiki which only they can edit.
<i>Workshop</i>	it enables the collection, review and peer assessment of students' work.
<i>File</i>	it enables a teacher to provide a file as a course resource.
<i>Book</i>	it enables a teacher to create a multi-page resource in a book-like format, with chapters and subchapters.
<i>Folder</i>	it enables a teacher to display a number of related files inside a single folder, reducing scrolling on the course page.
<i>Label</i>	it enables text and multimedia to be inserted into the course page in between links to other resources and activities.
<i>Gallery</i>	it enables participants to view a gallery of images.
<i>Page</i>	it enables a teacher to create a web page resource using the text editor.
<i>URL</i>	it enables a teacher to provide a web link as a course resource.
<i>Game</i>	it enables a teacher to game to their course.

(Moodle platform). These manipulations include the creation/modification/deletion of activities as well as other specific types of manipulations such as sending messages on chat or forum, grading students, adding events on calendar, etc. The table 5.2 describes all these features and gives the mean and standard deviation(Std) of each.

Table 5.2 – Description of the final dataset variables.

Variable	Description : The average number of	Mean	Std
<i>all_links</i>	teacher's manipulations of links in the course sections, labels or URL.	4.01	10.40
<i>assignment</i>	teacher's manipulations of assignments.	0.36	0.77
<i>attendance</i>	teacher's manipulations of the attendance activity.	0.0009	0.02
<i>book</i>	teacher's manipulations of the book resource.	0.005	0.17
<i>calendar</i>	teacher's manipulations of calendar.	1.86	4.91
<i>chat</i>	teacher's manipulations of chats.	0.03	0.20
<i>chat_message</i>	chat messages sent by the teacher.	0.61	3.84
<i>choice</i>	teacher's manipulations of the choice activity.	0.01	0.10
<i>course_format</i>	teacher's manipulations of the course format.	1.21	0.34
<i>data</i>	teacher's manipulations of the database activity.	0.006	0.07
<i>file</i>	teacher's manipulations of the file resource.	5.82	10.31
<i>folder</i>	teacher's manipulations of the folder resource.	0.99	2.55
<i>forum</i>	teacher's manipulations of forums.	0.32	0.99
<i>forum_discussion</i>	teacher's manipulations of the forum discussions.	0.75	3.43
<i>forum_post</i>	forum posts added by the teacher.	2.41	21.44
<i>gallery</i>	teacher's manipulations of the gallery resource.	0.03	0.60
<i>game</i>	teacher's manipulations of games.	0.01	0.24
<i>glossary</i>	teacher's manipulations of the glossary activity.	0.01	0.17
<i>grade</i>	teacher's manipulations of grades.	1.40	3.86
<i>img</i>	image added by the teacher in the course sections.	0.19	1.00
<i>label</i>	teacher's manipulations of the label resource.	1.5	5.63
<i>lesson</i>	teacher's manipulations of the lesson activity.	0.11	0.46
<i>lti</i>	teacher's manipulations of the external tools.	0.002	0.04
<i>page</i>	teacher's manipulations of the page resource.	0.47	1.52
<i>quiz</i>	teacher's manipulations of quizzes.	0.34	1.21
<i>survey</i>	teacher's manipulations of the survey activity.	0.0002	0.003
<i>url</i>	teacher's manipulations of the URL resource.	1.46	4.44
<i>via</i>	teacher's manipulations of the via activity.	0.02	0.15
<i>wiki</i>	teacher's manipulations of the wiki activity.	0.05	0.37
<i>workshop</i>	teacher's manipulations of the workshop activity.	0.007	0.14

5.2.1 Data preprocessing

Before starting the data analysis, we first performed a preprocessing phase through 3 different steps as shown in the figure 5.3. A Feature selection stage allowed to choose a subset of the most important features while trying to retain as much information as possible. To do this, we conducted a variance analysis since datasets require a high variance to increase the performance of models applied to data. It shows how spread out the distribution is and indicates the average squared distance from the mean. Therefore, we used the *variance threshold*² approach that removes all features below a certain variance threshold (low variance). By default, it removes all zero-variance features, i.e. constant features that have the same value in all samples.

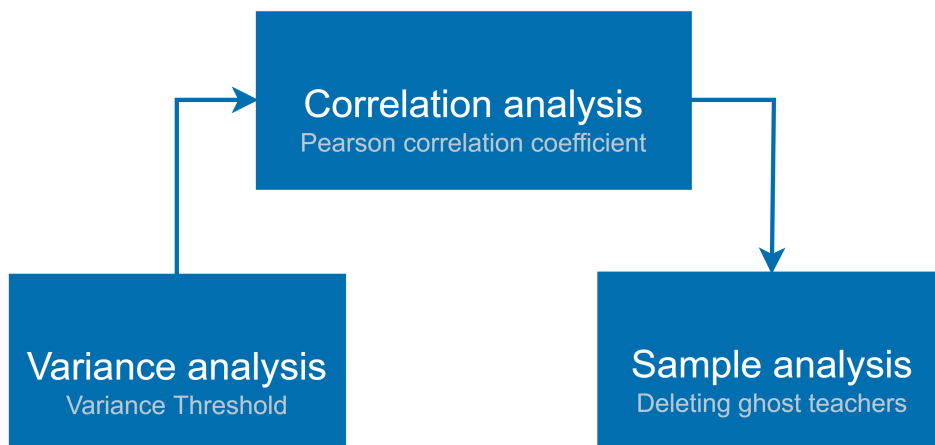


Figure 5.3 – Data preprocessing.

We then tested multiple values to remove both constant and quasi-constant features:

- threshold = 0.1 (dropping columns where 90% of values are similar): 11 features have been removed
- threshold = 0.2 (dropping columns where 80% of values are similar): 13 features have been removed.
- threshold = 0.3 (dropping columns where 70% of values are similar): 15 features have been removed.
- threshold = 0.4 (dropping columns where 60% of values are similar): 15 features have been removed.

2. https://scikit-learn.org/stable/modules/generated/sklearn.feature_selection.VarianceThreshold.html

- threshold = 0.5 (dropping columns where 50% of values are similar): 16 features have been removed.

Features with higher variance may contain more useful information and yield more relevant results. However, we did not want to eliminate a lot of features. Thus, we tried to keep as many as possible with a high variance. This may provide us with a clean dataset as well as a rich analysis according to several features. On the other hand, we noticed that a threshold of 0.3 or 0.4 gives the same results by eliminating all columns with 70% or 60% of similar values. Thus, we opted for the threshold that keeps 15 features with a variance greater than 0.3. It also should be stated that this approach does not take into account the relationship between variables, which is one of the drawbacks of such methods. The retained features are: *course_format*, *file*, *all_links*, *label*, *url*, *page*, *forum_discussion*, *folder*, *calendar*, *forum*, *grade*, *assignment*, *lesson*, *quiz*, *forum_post*, *wiki*, *chat*, *chat_message*, *img*, *via*, *glossary*, *choice*, *gallery*, *data*, *game*, *workshop*, *lti*, *attendance*, *survey*, *book*. We represent deleted variables by a red color in the table 5.2.

To complete the variance analysis, we performed a second filtering step to remove variables highly correlated to each other which therefore represent the same information. For this purpose, we used the correlation matrix which allows to measure the linear relationship between each pair of variables using the Pearson correlation coefficient (r). It is known as the most frequently used to measure the association between variables (Armstrong 2019). It is based on the covariance method that allows to study the simultaneous variations of two variables with respect to their average. Its values may range from -1 to +1. If both variables tend to increase and decrease together, the correlation value is positive. If one variable increases while the other decreases, the correlation value is negative. A high and positive r value indicates that the variables are measuring the same characteristic. If they are not highly correlated, variables may be measuring different characteristics or they may not be clearly defined.

The results reveal a strong correlation between two pairs of variables ($r > 0.8$) as illustrated in the figure 5.4:

- $r(\textit{label}, \textit{all_links}) = 0.89$
- $r(\textit{forum_discussion}, \textit{forum_post}) = 0.87$

Two variables appeared to be redundant: *label* and *forum_discussion* as they were respectively correlated to the overall number of links to external resources and the number of forum posts from the teacher. The *all_links* feature includes links the teacher has added

to a section, url or label activity ($all_links = labels + section_links + url$) therefore we eliminate the label variable since the information is still present. For the second couple, we remove the *forum_discussion* variable because a forum discussion is also considered as a post but the reverse is not true. These deleted variables are described by a yellow color in the table 5.2.

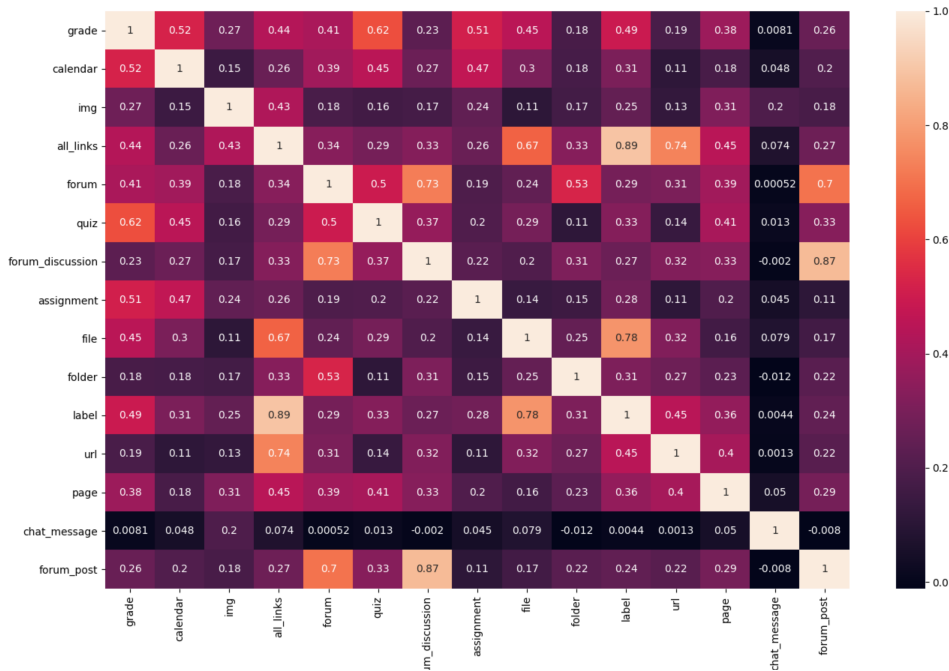


Figure 5.4 – Correlation matrix.

The last step aimed to eliminate “ghost teachers” who are considered as course editors but have only performed very few actions on the course. Therefore, we calculated the number of non-zero variables for each teacher, and found that most of them (487 teachers represented by the red line in figure 5.5) have at least 9 non-zero variables, hence we eliminated those who have more than 6 null values, and retained the 585 teachers left. This filtering allowed us to only retain teachers who use the platform more or less regularly and thus prevent any bias in the statistical analysis results that we will present in the following of this manuscript.

The final dataset is composed of 585 instances and 13 variables described by a green color in the table 5.2.

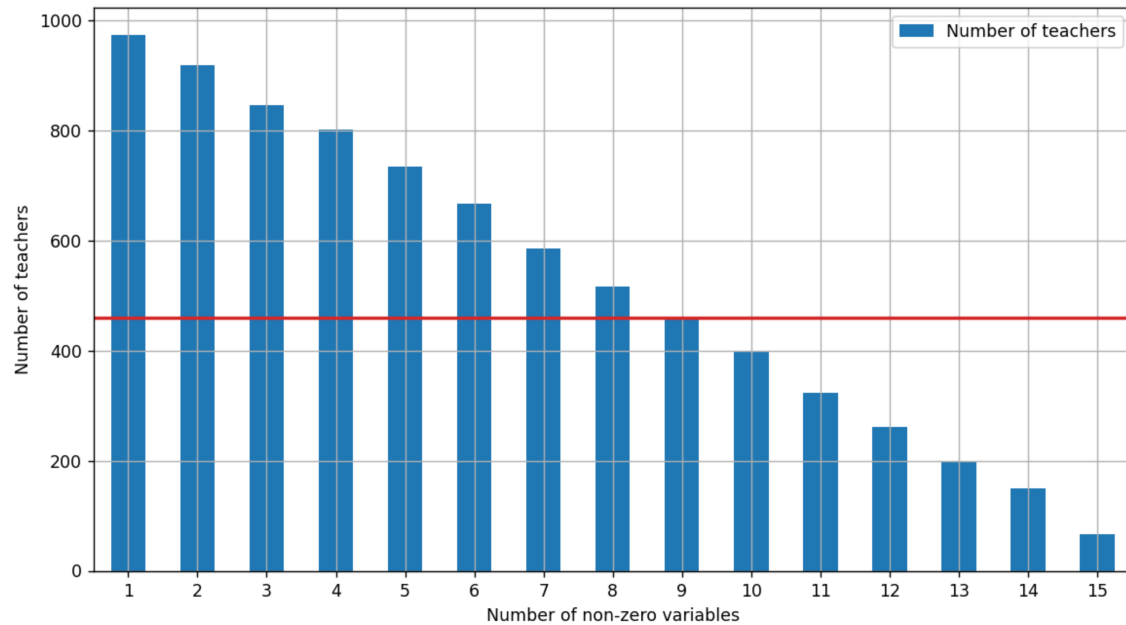


Figure 5.5 – The number of teachers per the number of non-zero variables.

5.2.2 Principal component analysis

In order to detect types of LMS use by teachers, we have conducted a PCA. It is a dimensionality-reduction method that is often used to transform high-dimensional datasets into lower-dimensional ones while retaining as much information as possible. In TEL, it is a commonly used method (Baby et al. 2016; Falfushynska et al. 2021), we have employed it to detect distinct patterns of LMS use by teachers without losing relevant information.

PCA is a parametric method that require to specify the number of components (dimensions) in order to compute the model. Different approaches allow to determine this number to ensure the best balance between information loss (the lower the number of components is, the more we might loose information) and model complexity (the higher the number of component is, the more complex the model will be to interpret). For the purpose of finding the best number of components, we used the criterion of eigenvalue (Tamura et al. 2007): each component must explain the value of at least one variable, and therefore it indicates that only components with eigenvalues greater than 1 should be retained. According to this criterion, we have been able to identify 5 variables (*their eigenvalues* > 1). Thus, the best number of principal components of our dataset is 5, explaining 72% of the total

variance (the information contained in the dataset) as illustrated in figure 5.6.

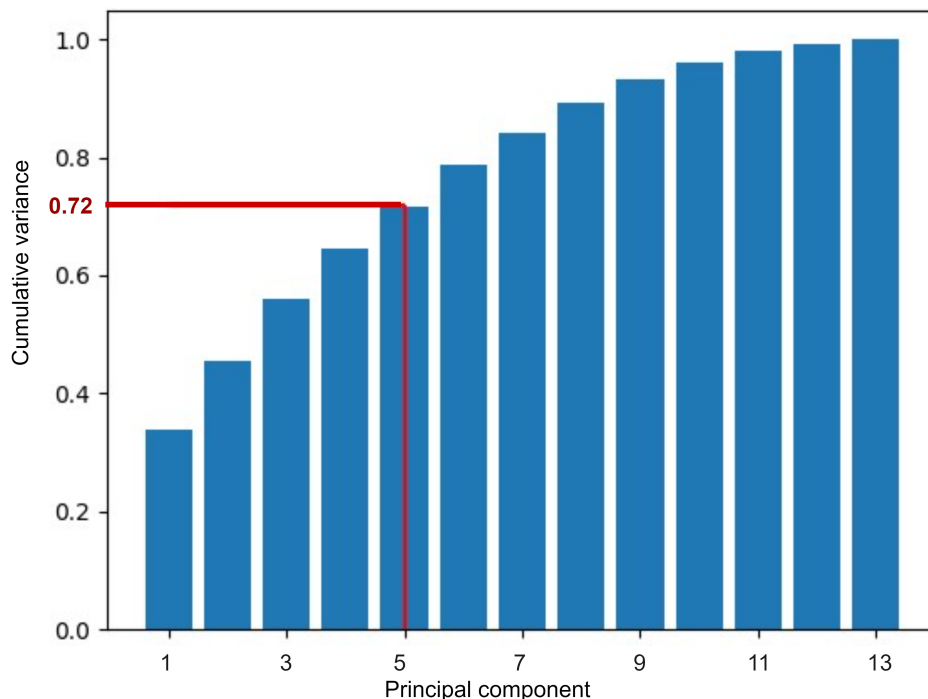


Figure 5.6 – Total variance captured by principal components.

To interpret our principal components, we calculated the contribution (CTR) of each variable in their construction (see table 5.3). This parameter is calculated based on the correlation of variables with each component and thus it allows to identify the influence of these variables in each principal component. By studying these contributions, we were able to interpret and describe our components as shown in table 5.4.

The first component (*comp 1*) represents the global use of the platform with a consistent use of most platform tools. In other words, almost all variables are involved with the same polarity and regardless of the type of activities exploited, which synthesizes the overall use of the LMS. The contribution of all these variables ranges from 7.07% to 8.99% except for *chat_message* which has a low contribution of 3.03%. Thus, it seems that most teachers with a global use of the platform exploit the chat less than other tools of the platform. It can be explained by the fact that forums have a high contribution (CTR=8.69%) and they can be used as an alternative communication tool.

The second component (*comp 2*) highlights the management of evaluation within the LMS. It gathers tools to manage assignments and submissions (*grade*, *quiz*, *assignment*),

with high contributions of 12%, 14.72%, 17.09% respectively. Moreover, it covers the use of calendars with 13.39% of contribution, which are mainly intended to manage deadlines for assignments and assessments.

The third component (*comp 3*) concerns exclusively the use of forums (*forum, forum_posts*) with high contributions of 19.38% and 20.82% respectively.

The fourth component (*comp 4*) represents essentially the use of chat activities (CTR=34.05%) and the exploitation of images in course sections (CTR=15.16%). Based on the fact that we have no theoretical support nor empirical insight to consider such odd association, we consider that this component represents the use of chats since it has a greater contribution and the relation between chats and images is coincidental.

The last component (*comp 5*) is based on the use of resources. It brings together tools used by teachers to support learning: *pages* (CTR= 23.07%) and *folders* (CTR=42.43%).

Table 5.3 – Contribution of variables in each component.

Variable	CTR1(%)	CTR2(%)	CTR3(%)	CTR4(%)	CTR5(%)
<i>grade</i>	8.83	12	4.11	3.56	1.14
<i>calendar</i>	7.17	13.39	4.08	3.75	4.51
<i>img</i>	7.07	8.3	6.64	15.16	3.04
<i>all_links</i>	8.99	7	8.05	6.29	2.19
<i>forum</i>	8.69	4.79	19.38	2.96	2.24
<i>quiz</i>	8.15	14.72	3.86	5.22	6.45
<i>assignment</i>	7.17	17.09	4.64	4.03	8.42
<i>file</i>	8.74	3.79	7.03	8.16	1.94
<i>folder</i>	8.12	4.9	6.64	2.57	42.43
<i>url</i>	7.54	4.87	2.29	2.58	1.35
<i>page</i>	7.95	3.08	3.13	4.32	23.07
<i>chat_message</i>	3.03	1.08	9.32	34.05	2.94
<i>forum_post</i>	8.54	4.98	20.82	7.34	0.27
Total	100	100	100	100	100

Regarding the information present in each component, the first one expresses the highest variance (33.97% of the total information). This reveals that most teachers of our university have a global use of the platform. While this use may be significant for some teachers, it is either very low or almost non-existent for others. The second component represents 11.65% of the total variance, which means that student evaluation tools are used by a large proportion of the remaining teachers. Further, in third position, they use communication tools (forum and chat with 10.42% and 8.61% of variance respectively).

Finally, the last component expresses 7.43% of the total variance, which corresponds to teachers who use different resources to enrich their courses (page, folder).

Table 5.4 – PCA results

Component	Variance (%)	Description
<i>Comp 1</i>	33.97	overall use of the platform with consistent use of most tools.
<i>Comp 2</i>	11.56	management of the evaluation within the LMS (assignments and submissions).
<i>Comp 3</i>	10.42	use of forums.
<i>Comp 4</i>	8.61	use of chats and exploitation of images in course sections.
<i>Comp 5</i>	7.43	use of resources.
<i>Total</i>	72	/

5.3 Qualitative study

The qualitative study aims to validate our interpretation of the previous quantitative analysis and refine its results. It also provides new insights regarding teacher behavior that could not be identified statistically. To do this, we carried out semi-structured interviews with PEs at our University. They were conducted separately with 3 engineers on the same day and each lasted 40 to 50 minutes. Two engineers have 2 years of experience on the main Moodle LMS provided, which our work is based on. The third engineer has 6 years of experience on the second instance of Moodle which offers more features than the first one, but it is dedicated only to remote learning. However, as we do not have access to this platform, it is out of the scope of this work. All interviews were tape-recorded, transcribed, and analyzed by 2 researchers who compared different responses by grouping similar ones and detecting particular cases.

Prior to the interviews, we prepared the interview guide that included the different questions, classified according to their themes:

- **Introduction:** mutual presentation, research objectives, PE biographies and competencies.
- **Implementation of pedagogical scenarios on LMS:** method used by PEs to implement teachers' practices.

- **Use of the LMS by teachers:** PEs' perception of teachers' LMS use, difficulties encountered by teachers to implement their practices, teachers' profiles observed, suggested indicators to define and detect these profiles.
- **Evaluation of variables used in the first analysis:** opinion about variables used in the first quantitative analysis, discussion about other variables that might be relevant.
- **Evaluation of the obtained groups of teachers:** consistency of the identified groups, and usability of the model.
- **Tool and expectations:** vision and expectations of PEs regarding an application that is intended for them.

Throughout the interviews, no contradictory statements were detected, and there was a consensus on most of the conclusions. For the implementation of pedagogical scenarios, they mentioned not using any predefined formalism but rather adapt to the teacher's choice. This is mainly due to the fact that teachers are not open nor ready to change their traditional practices. As a result, we exclude proposing formalisms related to LMSs in order to help them to integrate new pedagogical practices which they do not use (e.g. flipped classroom). However, we still can assist them in integrating their own designs into the University's LMS.

Regarding LMS use, they indicated that it is underused to its potential. One engineer specified that its use is mainly in science faculty with people who are "not afraid of computers" and that this use is very variable from one teacher to another. The difficulties experienced by teachers according to these engineers are mainly due to insufficient knowledge of the platform and to the lack of time for learning. This observation is in line with the different results we found in the state of the art. Another engineer added that teachers only see the LMS as a computer tool, which prevents them from improving their techno-pedagogical skills. These results match those found in literature, leading us to offer support tools in order to change the current situation. This seems important because LMSs are nowadays essential but their use is not always obvious.

The different profiles of LMS use by teachers, according to PEs, are (i) resource repository, (ii) communication, (iii) evaluation, (iv) collaboration and (v) feedback. Recently, they have noticed a demand for more (vi) fun and attractive activities. The (i) resource, (ii) communication and (iii) evaluation groups have already been identified by the quantitative study. While the first one reflects the fifth component (use of resources), the second group can be represented by the third component (forum use) as well as the fourth (chat

use). The evaluation group represents the second component (management of the evaluation within the LMS). However, the quantitative analysis could not detect the other groups ((iv) collaboration, (v) feedback and (vi) attractive activities). This might be related to the small number of teachers who use them, but they are still worth studying. Moreover, PEs proposed some indicators to assess these profiles which revolve around activities' frequency of consultation by students, the use of links, individual or collective resources and quizzes. These have already been taken into consideration in the quantitative analysis except for student data. However, we made the choice for this work to leave out student data in order to provide findings for teachers using only their data (as explained in the chapter 3).

With respect to the first quantitative analysis, PEs encouraged us to correct some variables' computation. While we used the activity *url* proposed in the LMS to compute the number of external references a course may have, engineers explained that many reference to external content were directly written in the content of labels or section summaries. Furthermore, they suggested adding some activities that were not collected at the time which are game-type ones and images. They also emphasized the importance of including the collected feedback using survey or choice activities, that were unfortunately removed during the preprocessing phase due to its low variance. These remarks showed the importance of improving the quantitative analysis and in particular proposing a model that allows to properly describe the use of the LMS by teachers. This would be achieved by taking into account not only the refined quantitative analysis results, but also other features and groups proposed by PEs which are not used too much to appear in the statistical results.

PEs expressed, once they saw teacher groups, their interest in getting to know the very active teachers. They were actually eager to invite them to have a discussion and get their feedback. At the end, they described their needs regarding the exploitation of our results. It consists mainly in the necessity to have elements to better support teachers without being drowned in a mass of numbers. Furthermore, they wanted to have insights on how good course environments are to engage students in learning, and visualize the results by department and by discipline. On the COVID part, they were curious to see the changes in the LMS use. Given these expectations, we decided to offer PEs a tool that would allow them to detect teachers who need help and those who are using the LMS with ease. In addition, this tool would provide a simple way to compare LMS use by specialties and departments.

As explained above, we aim at finding the best way that can describe teachers' use of the university's LMS. By leveraging results from the two studies we conducted (quantitative and qualitative), we were able to define a model that provides a full picture of teachers' use of our University's LMS and thus it describes their behavior while using it. The next section presents in detail this model.

5.4 Behavioral model

The behavioral model describes within six axes the behavior of teachers in a comprehensive way. It considers previously discovered components from PCA and findings from interviews we had with PEs as shown in figure 5.7. All PCA components were reviewed during the qualitative analysis. Thus, by combining the "chat" and "forum" components in one axis because they are both communication tools, and adding teachers' groups identified by PEs that we could not detect by the first analysis (reflection, collaboration, interactivity and gamification), we finally obtained a 6 axis model. We did not consider the first component of the PCA because it represents the global use of the LMS (all axis).

The purpose of this model is to provide self-awareness and support teachers' self-evaluation. It allows them to get an overview of their LMS use along several dimensions, to reflect and become aware of their own practices. Therefore, it enables teachers to determine their weaknesses and strengths regarding their techno-pedagogical skills. This model includes features that can be used to represent their current situation, and others that reflect little or no use, but may prove important in their future practices.

5.4.1 Evaluation

The evaluation axis represents the different tools used by the teacher to assess their students. It reflects the second component of the PCA (management of the evaluation within the LMS). This particular component was already present in PEs mind before presenting them the results of our quantitative analysis. Its objective is to evaluate how the teacher benefits from the digital environment to organise and implement students' assessment. It includes the *quiz* and *assignment* variables that offer different ways to assess students and provide them with formative feedback. The *grade* variable to provide summative feedback and *calendar* for organization (e.g. deadlines settings). The last variable is the *attendance* which is used to evaluate students' presence in a course.

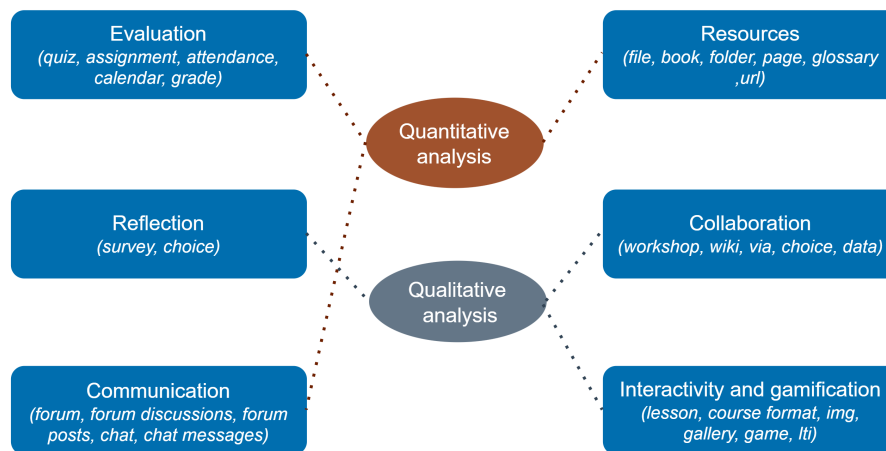


Figure 5.7 – The main source of each model axis.

5.4.2 Reflection

The reflection axis concerns LMS features that can provide teachers with a way to get feedback from students on their teaching and the digital functionalities they use. Both variables *survey* and *choice* reveal this particular exploitation of the LMS. So far, they are used marginally and do not appear in the statistical findings. However, they should be taken into account because reflection was considered as an important dimension in the interviews we had with PEs.

5.4.3 Communication

This axis is devoted to the different means of communication used by teachers to facilitate the transfer of information to students and also to improve the sharing between them. It brings together the third (forum use) and the fourth component (chat use) of the PCA. Therefore, it includes forum and chat related variables which were also validated by PEs (*forum, forum_discussion, forum_posts, chat and chat_messages*).

5.4.4 Resources

The resources axis refers to items that a teacher can use to support learning. They are intended to reinforce knowledge and help students better acquire information. Therefore, this axis includes the *file, book, folder, page, glossary and url* variables. It was designed

based on the the PCA fifth component (use of resources), other variables mentioned were added thanks to interviews with PEs.

5.4.5 Collaboration

This axis concerns the promotion of collaboration between students through different LMS features. It includes the *workshop*, *wiki*, *via*, *choice et data* variables, identified by the qualitative analysis. The *workshop* functionality allows for the collection, review and peer evaluation of student work. While *wiki* activity can be collaborative with everyone being able to edit it, the *choice* one can be used as a quick poll to stimulate thinking or collaborate on building ideas. On the other hand, *via* activity allows the creation of synchronous meetings in a virtual classroom. Finally, *data* allows participants to create, maintain and search a collection of entries (i.e. records). The latter can be rated by teachers or students (peer evaluation).

5.4.6 Interactivity and gamification

This last axis gathers the interactive or playful activities used by teachers to animate their courses and make them more attractive. It is also identified on the basis of the qualitative analysis and gathers *lesson*, *course_format*, *img*, *gallery*, *game*, *lti* features. They all refer to activities that raise interactivity or gamification. While *lessons* enable the personalization of course sequences, *galleries* allow to expose collections of pictures with the possibility to comment on them. On the other hand, *lti* allows to include external activities using the LTI protocol. It enables communication between various e-learning applications and tools, including sharing learning resources and activities on other websites. Version 2 of this standard also allows for any type of trace to be sent back to the LMS for integration into our LRS in the context of the activity (course). Eventually, we perceived the modification of the *course_format* itself as evidence of the teacher's reflection on how students would interact with the course.

5.5 Synthesis

In this chapter, we first detailed the quantitative analysis we conducted on four years of teachers' activities using the university's LMS. Then, we explored the qualitative study that we did based on interviews with three pedagogical engineers. The objective of the first

study was to find out what teachers really do on the LMS, through the analysis of their traces. The second study aimed to collect information that could be useful to understand the current behavior of teachers from PEs point of view, as they have experience with teachers.

The results showed that:

- In general, the institutional LMS is not used to its potential.
- 5 components of LMS use were identified through the PCA. By combining forum and chat components and excluding the first one, which represents the global use of the LMS, we have designed 3 axis: communication, resources and evaluation.
- 3 additional axis were mentioned by pedagogical engineers: reflection, collaboration as well as interactivity and gamification.

The fact that our University's LMS is not used enough is consistent with most other universities, as we saw in the state of the art. This indicates how important our work is in helping to find a solution that can change the current situation.

Leveraging results from both quantitative and qualitative studies allowed us to design an axis-based model. It categorizes teachers' use of the platform in order to support teachers self-awareness and set the stage for their self-evaluation. The behavioral model depicts teachers actions in the LMS along several axis (evaluation, reflection, communication, collaboration, resources, interactivity and gamification). The method we used to design this model aims at being generic since it is decoupled from any technological environment. However, the model itself aims at describing the teacher's behavior in a specific LMS, which gives it a local scope related to the technological choice. As institutions have different needs and preferences, each Moodle is distinct. This means that they do not have the same functionalities and therefore not the same data we can retrieve. Moreover, the use of LMSs is related to several factors such as the complexity of the platform itself, teachers performances, the support and assistance they get, etc. Thus, axes that can be designed may not be the same as well.

Nevertheless, the identification method of a teacher behavioral model in the context of another university remains the same and it is valid for any Moodle. This just requires collecting actions performed by teachers on the LMS for statistical analysis. Then, it is necessary to validate and enrich these results by conducting a qualitative study involving experts and/or teachers. By combining the outcomes, a behavioral model can be defined.

This model is very important to give a global view of teachers' use of the LMS. In contrast, it should be leveraged to provide TA indicators and recommendations that

can better support teachers' self-evaluation and help them improving their practices. We therefore detail indicators and recommender systems that we propose in the following chapter.

MODEL EXPLOITATION

The model we have designed provides a way to describe how teachers use the LMS through different pedagogical axes. However, it can be further leveraged to more accurately support teachers' self-awareness and self-evaluation. Therefore, we designed several TA indicators to provide teachers with self and social awareness. Then, we proposed various recommender systems to help them to improve their mastery of LMS. This chapter details how we carried out these steps, which are the last ones related to the data analysis phase, as shown in figure 6.1.

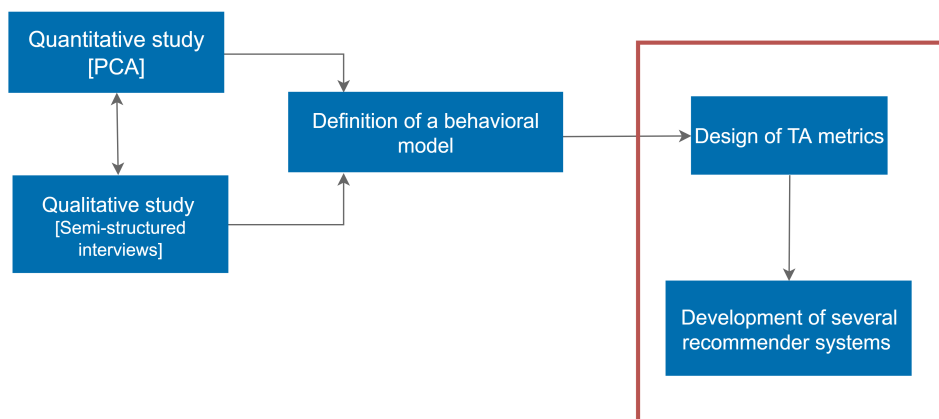


Figure 6.1 – indicator and recommendation steps.

6.1 Teaching analytics indicators

In this section, we explain in detail the different TA metrics that we have designed.

6.1.1 LMS usage trends

The LMS usage trends metric provides teachers with a current view of their position (regarding use of LMS) relative to their colleagues. The purpose of this indicator is to support teachers' social awareness and to help them better self-evaluate their technopedagogical skills in the University's LMS. The proposal of this indicator was inspired by the social comparison theory (SCT) introduced by the psychologist Leon Festinger in 1954. It suggests that people have an innate drive to compare themselves to others in order to evaluate their own opinions and abilities (Festinger 1954). In other words, comparison with others provides a way for individuals to measure their personal development, to motivate themselves and to develop a more positive self-image (Suls et al. 2002). Therefore, we aim here to propose an indicator that allows teachers to determine their tendency to use the LMS compared to their colleagues and according to each axis of the behavioral model (for a more refined comparison).

We performed a clustering analysis by axis to distinguish groups of teachers based on their trends (patterns) to use the institutional LMS. For each axis, we created a dataset using features that were identified during the definition of our model (figure 5.7). Then, we applied the same preprocessing steps we used in our quantitative analysis, by axis as well (section 5.2.1). This phase allow to transform data into a format that can be processed more easily and efficiently in machine learning (ML) algorithms. It therefore consists of filtering variables that would decrease the model performance due to their low variances. For the six axes, we chose to remove variables whose 80% of values are similar (threshold=0.2). This is because we didn't have many features per axis and we needed to avoid losing a lot of variables. Next, we have removed features with high correlation between them ($r > 0.8$). We completed the preprocessing phase by eliminating ghost teachers, who have very little action according to each axis and thus could be detected as noise by our models. The final datasets are described by the table 6.1.

Regarding clustering algorithms, we chose to study those that are most known and used in educational data mining (Trivedi et al. 2020; Whitmer et al. 2016; Il-Hyun et al. 2017; Zhang et al. 2016): K-Means, Dbscan, Agglomerative clustering and Gaussian Mixture. K-means¹ is an iterative algorithm that minimizes the distance sum between each individual and the cluster centroid. Whereas Dbscan² is an algorithm that defines clusters using local density estimation. It also allows to identify outliers because points

1. <https://scikit-learn.org/stable/modules/generated/sklearn.cluster.KMeans.html>

2. <https://scikit-learn.org/stable/modules/generated/sklearn.cluster.DBSCAN.html>

Table 6.1 – Description of each axis dataset.

Axe	Features	No. of samples	Mean	Std
<i>Evaluation</i>	<i>grade</i>	974	0.66	1.94
	<i>calendar</i>	974	0.91	2.50
	<i>quiz</i>	974	0.15	0.48
	<i>assignment</i>	974	0.22	0.51
<i>Reflection</i>	<i>choice</i>	75	1.77	1.50
<i>Communication</i>	<i>forum_post</i>	974	0.58	5.11
	<i>chat_message</i>	974	0.33	2.62
<i>Resources</i>	<i>file</i>	884	5.44	8.83
	<i>folder</i>	884	0.89	2.32
	<i>all_links</i>	884	1.87	5.43
	<i>page</i>	884	0.59	1.4
<i>Collaboration</i>	<i>workshop</i>	284	0.07	0.51
	<i>wiki</i>	284	1.11	2.58
	<i>via</i>	284	0.42	1.002
	<i>choice</i>	284	0.33	0.88
<i>Interactivity and gamification</i>	<i>img</i>	974	0.07	0.51

that do not belong to any cluster get their own class (-1). Agglomerative clustering³ is a type of hierarchical clustering algorithm that uses a bottom-up approach. Each data point starts in its own cluster, and then all are combined by taking the two most similar clusters each time and merging them. Finally, Gaussian Mixture⁴(GMM) is a probabilistic model which assumes that all data points are generated from a mixture of a limited number of Gaussian distributions with unknown parameters (called kernels).

To set the best number of clusters for each model, we used the silhouette score (S). It is a metric that enables to measure the quality of a clustering algorithm and ranges from -1 (worst) to +1 (best). A high value indicates that the sample (the teacher in our case) is well matched to its own cluster and poorly matched to neighboring clusters.

Based on the cleaned datasets, we tested the above mentioned clustering algorithms for each axis of our behavioral model. We then selected the best model based on silhouette score and clusters consistency. The results are exposed in table 6.2, with S the silhouette score, N the number of clusters and O the number of outliers for DbSCAN.

For each axis, these models converge towards a detection of particular teachers (active teachers and non-active teachers), and not towards a regular or homogeneous classifica-

3. <https://scikit-learn.org/stable/modules/generated/sklearn.cluster.AgglomerativeClustering.html>

4. <https://scikit-learn.org/stable/modules/mixture.html>

Table 6.2 – Results of the clustering analysis

Axis	K-means	Dbscan	Hierarchical Clust.	Gaussian mixt.
A.1	S=0.81, N=2	S=0.85, N=1, O=3	S=0.84, N=2	S=0.2, N=2
A.2	S=0.91, N=13	S=0.68, N=1, O=11	S=0.81, N=6	S=0.89, N=15
A.3	S=0.84, N=2	S=0.92, N=1, O=2	S=0.77, N=2	S=0.7, N=2
A.4	S=0.83, N=2	S=0.91, N=1, O=1	S=0.85, N=2	S=0.59, N=2
A.5	S=0.76, N=2	S=0.81, N=1, O=1	S=0.76, N=2	S=0.34, N=2
A.6	S=0.98, N=2	S=0.98, N=1, O=3	S=0.98, N=2	S=0.87, N=2

tion. This result is consistent with other studies in literature so far (Park et al. 2017).

The second axis “Reflection”, initially characterized by *survey* and *choice*, contains only one feature that is *choice*, because *survey* was removed in the preprocessing phase due to its low variance. This explains the number of clusters obtained by the four algorithms, which classified the use of choices by teachers from most to least active.

Models of the remaining axes consistently returned two clusters that separate the most active teachers from those who are not or slightly active. For instance, after the analysis of the evaluation axis, Dbscan gave the best results with a group of teachers that use evaluation tools minimally and three particular teachers that use most of these tools in a homogeneous and intensive way.

Most algorithms gave the same number of clusters that we could interpret in the same way. One cluster includes teachers with intensive use of the different axes functionalities and the other one for the opposite case (low use). Therefore, we decided to select only one algorithm for each axis.

The best silhouette scores were obtained by Dbscan algorithm, except for the second axis which was Kmeans. For this reason, we chose Dbscan algorithm because it is capable of detecting specific instances of the platform use (teacher groups and outliers). The figure 6.2 illustrates these clusters by highlighting outliers (active teachers) in a blue color. For each axis, we plotted the two identified teacher groups using a 2D representation. This means that we have represented only 2 features out of the total number of features in each axis.

For example, the evaluation axis shows that there are 3 teachers in the University of Le Mans who use the different evaluation features intensively (quiz, assignment, attendance, calendar, grade) and the rest of the teachers have a non-intensive use.

This first metric “LMS usage trends” allows to detect groups and particular profiles (outliers) of teachers according to each axis of our behavioral model. Thus, teachers can identify the axes on which they have an intensive use and those on which they are not active. It also enables them to position themselves in relation to their colleagues as this indicator is based on the global use of the platform. In other words, a teacher is considered non-active on an axis because there are others who have more intensive use on the same axis. This could help teachers to evaluate themselves based on social comparison. While this social comparison can motivate people to improve, it can also promote judgemental, biased and overly competitive attitudes (because of differences between individuals) (Dijkstra et al. 2008). Therefore, it is important to complement this indicator with others that relate only to the teacher in order to enable a more objective evaluation.

6.1.2 Usage scores

The previous metric provides some indications of teachers’ current level of LMS mastery relative to the group. However, it focuses only on social awareness by considering teachers’ skills relative to their colleagues. Furthermore, it discards some features due to the preprocessing steps required in clustering methods. These features are still important (even if they are not used by many teachers) and allow for the identification of other use cases in the LMS.

To overcome these problems, we propose two complementary metrics in order to promote teachers’ self-awareness. They both allow to measure how the teacher profits from the LMS, based on the model we have designed as well. However, this time, these two metrics only relate to the teacher and their own use of the platform. They also take into account all features that were identified for each axis. Each of these metrics complements the other and, thus, combining them with the first one (LMS usage trends) could enable teachers to be more aware of their practices in the University’s LMS and refine their self-evaluation.

In this section, we present two usage scores that outline how the teacher appropriates the LMS along each axis of our behavioral model: curiosity and homogeneity score.

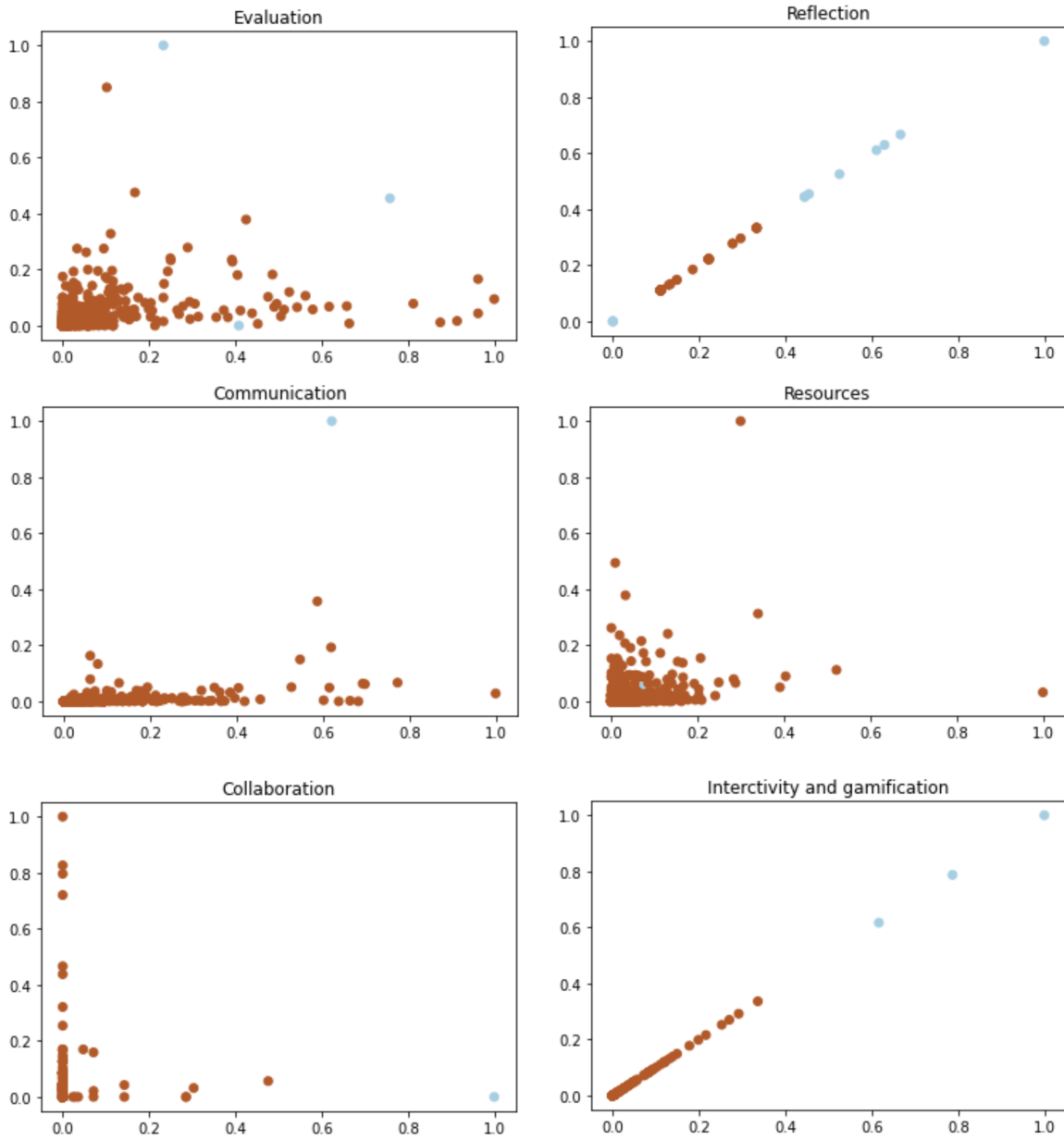


Figure 6.2 – Clusters detected by DbSCAN.

Curiosity score

This score captures the diversity of LMS use based on the different features of an axis. It provides the teacher with an indication of their curiosity to leverage the platform’s different functionalities. Counting the number of non null variables over all the teacher’s courses per axis, we formalized this score by the following equation:

$$curiosity_a(t) = \frac{\sum_{i=1}^{m_a} x_{t,i}}{m_a}, \text{ with } x_{t,i} = \begin{cases} 1 & \text{if } \sum_{c=1}^{C_t} x_{t,i,c} > 0 \\ 0 & \text{otherwise.} \end{cases} \quad (6.1)$$

With $x_{t,i,c}$ the value of the feature $i \in [1, m_a]$ (m_a the num. of features for the axis a) for the teacher t in the course $c \in [1, C_t]$ and C_t the number of courses where the teacher t has at least one non null variable.

While the LMS usage trends indicator allows the teacher to see if they have intensive use of a specific axis, it does not provide details on the functionalities of this axis involved in the use detected by the clustering analysis. We assume that having such information will increase teachers’ self-awareness and, particularly, encourage them to discover other functionalities within each axis.

According to (Litman 2008), curiosity refers to “the anticipated pleasure of acquiring new knowledge and discoveries, or the individual’s need to reduce and eliminate undesirable states of ignorance”. This means that curious individuals have an advantage in terms of evolution over others. Furthermore, curiosity has been considered one of the most essential component of learning (Kesner Baruch et al. 2016), meaning that individuals who are more interested in a particular content are able to process more deeply information about it. In literature, this concept has received more focus to motivate students and improve their learning by measuring their curiosity using multiple indicators (inquiry, note taking, feedback, sensorimotor behaviors, figurative expressions, etc.) (Kesner Baruch et al. 2016; Nurhayati et al. 2021). However, teachers’ curiosity has not been studied yet in the context of LMS, leading us to measure their curiosity in using different LMS features as an indicator of self-awareness. We have chosen to calculate this curiosity by counting the number of features that have been manipulated at least once by the teacher. The objective of this score is to give the teacher a simple and explainable way to assess their curiosity. As a result, teachers can evaluate the extent to which they exploit the various features of LMS. However, this exploitation can differ from one course to another. Therefore, teachers may also need to have this information in order to better evaluate their use. The next

score is dedicated to this purpose.

Homogeneity score

This score considers the homogeneity of the teacher's use of the LMS with respect to their courses. In other terms, it indicates the frequency with which a teacher exploits the functionalities related to an axis in the context of their courses. It is formulated by adding, for each feature, the number of courses where the teacher has already manipulated the feature at least once. Then, we calculate the average per axis, as the following formula shows (using the previous symbols):

$$homogeneity_a(t) = \frac{\sum_{c=1}^{C_t} \sum_{i=1}^{m_a} x_{t,i,c}}{m_a \cdot C_t}, \text{ with } x_{t,i,c} = \begin{cases} 1 & \text{if } x_{t,i,c} > 0 \\ 0 & \text{otherwise.} \end{cases} \quad (6.2)$$

This indicator allows the teacher to determine whether its use has a similar and consistent nature across their courses or not. It is also based on the curiosity score since they have the same basic principle (counting features that have been used at least once by teachers). However, the homogeneity score aims at raising teachers' awareness of the consistency of their curiosity in relation to their courses. The two usage scores range from 0 to 1. To facilitate the interpretation of these scores, we have depicted them as a percentage. Taking the communication axis as an example: teachers who have already used all functionalities of this axis (chat, forum) will have a curiosity score of 100%. This means that they are considered as curious teachers regarding communication tools. On the other hand, if they use both forums and chats in all their courses, they will also have a homogeneity score of 100%. This indicates that they are consistent in their use of communication tools with their students. For example, the figure 6.3 shows how the different features of the evaluation axis were used by a teacher working on two courses. We notice that this teacher has tested all these functionalities in at least one course except the attendance feature. Therefore, they would have a curiosity score of 80%. On the other hand, the teacher is regular in their use of the assignments and calendar and therefore they would have a homogeneity score of 60%.

Having low scores in certain axes does not mean that teachers' practices are not good or that they must have better scores. Those indicators remain a self-awareness ones aiming to help teachers evaluate themselves as well. Therefore, it is entirely up to the teacher to decide whether or not they want to score higher depending on their courses, needs and



	quiz	assignment	attendance	calendar	grade
 Cours 1	✗	✓	✗	✓	✗
 Cours 2	✓	✓	✗	✓	✓

Figure 6.3 – Example of using features of the evaluation axis.

preferences.

6.2 Case study of Le Mans University

The first indicator (LMS usage trends) is completely related to Le Mans University. Thus, results of the DbSCAN algorithm provide the list of teachers with intensive or non intensive use according to each axis (as shown in the figure 6.2). The number of active teachers on at least one axis is 21 teachers, representing 2.15% of their total number. These results confirm the low use of the LMS by most teachers.

The LMS usage trends indicator can also be relevant for a different university context. A clustering analysis can be applied on the University's data by axis in order to detect the different usage patterns. The findings may lead to clusters that highlight certain practices within the axis (not necessarily the same ones that we found), e.g. a communication-based forum or an interactivity-based course structure, etc. However, the purpose of the indicator remains the same, i. e. promoting teachers' self-awareness about their use of the different features of each axis.

Regarding the two LMS usage scores, we calculated their values for each teacher of our University. The table 6.3 shows how teachers' scores are distributed regardless of the axis. The majority of teachers have scores below 40 (90.77% and 97.45% for curiosity and homogeneity scores respectively), while very few of them have values above 60 (3.18% and 0.35% for curiosity and homogeneity scores respectively). These results again confirm the low use of the LMS and the fact that it is not used to its full potential. Most teachers are not very curious to discover the different functionalities available in the LMS and for the used ones, teachers do not consistently exploit them in all their courses. For some

cases, teachers may not need all features to manage their courses. However, according to PEs, the main reason for this use is the difficulties teachers face in mastering the LMS (lack of time, complexity of the platform, lack of support, etc.). In contrast, we noticed that the curiosity score values are higher than those of homogeneity. This means that teachers do not exploit the platform in the same way to implement all their courses. It may be due to differences between courses and also to the fact that several teachers can be involved in the same course. The lead teacher is the one responsible for creating the course environment and therefore can affect the homogeneity score of the others.

Table 6.3 – Distribution of score values by teachers.

Score (s)	Percentage of teachers with $s < 40$	Percentage of teachers with $40 \leq s \leq 60$	Percentage of teachers with $s > 60$
Curiosity score	90.77%	6.04%	3.18%
Homogeneity score	97.45%	2.19%	0.35%

To further investigate usage scores, we compared their values with respect to each axis, as illustrated in the figure 6.4. It reveals that the best curiosity scores (indicated by the red and orange colors) were identified in the resources, evaluation, and communication axes. This corresponds to the results of PCA that has detected these three components and also to the interpretation of PEs. For the homogeneity score, values are lower (colored in dark and forest green) but nevertheless the best ones were also identified in the same previous axes. This means that the Umtice platform of Le Mans University is mainly used as a repository tool, to communicate with students and to evaluate them.

6.3 Recommender systems

Supporting teachers' self-awareness and self-evaluation is very important to help them engage in learning situations to improve their practices. However, providing support and assistance to accompany this learning process is also essential. For this purpose, we propose in this section, three recommender systems (RSs).

The following systems were chosen mostly on the basis of existing literature. As discussed in chapter 2, several works have emphasized the importance of the subjective norm in changing teachers' intention to use the LMS (Ajzen 1991; Coskuncay et al. 2013;

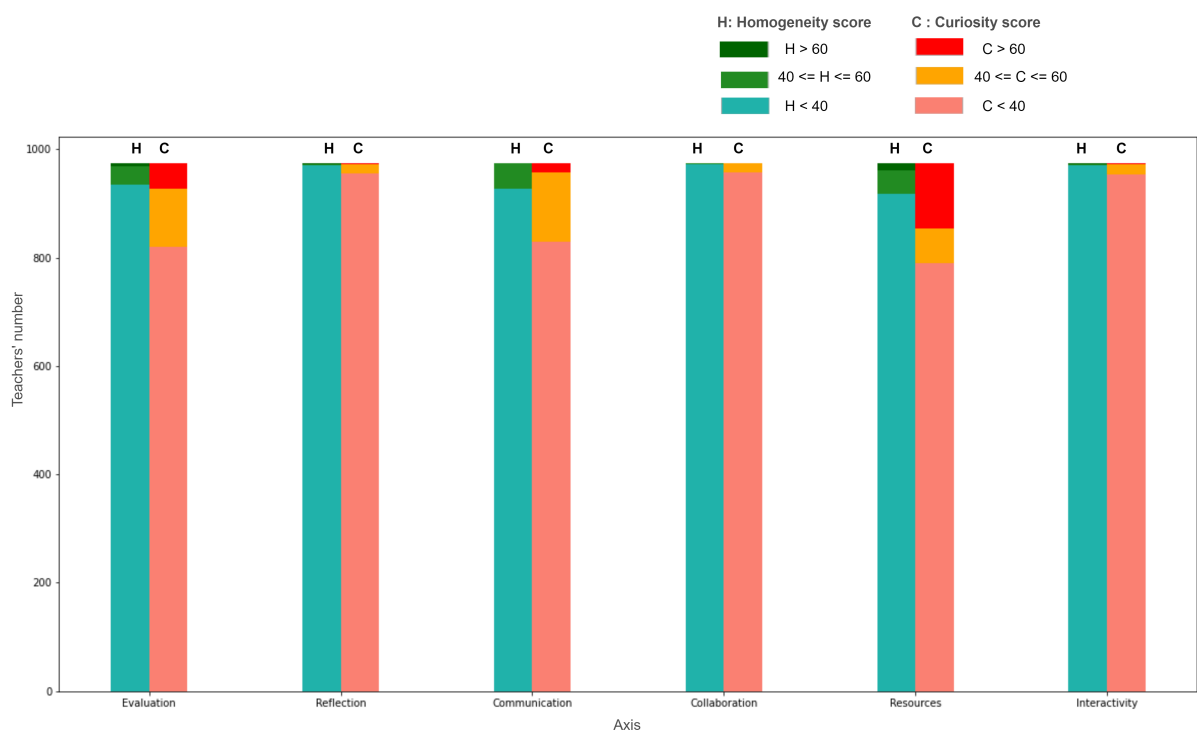


Figure 6.4 – University teachers' usage scores by axis.

Cigdem et al. 2015). It refers to an individual's beliefs about whether their peers and important people to them think a particular behavior is necessary. Furthermore, professional development frameworks have also encouraged peer support to improve the quality of the online teaching-learning process (Baran et al. 2014; Kopcha 2010). Therefore, we sought here to promote peer learning by assisting teachers in helping each other via the first RS. Moreover, we involved PEs since they are part of the teacher's entourage and they master the LMS (second RS). For autonomous teachers, we offer a third RS that provides them with some functionalities they can test by themselves (if needed).

Before presenting the different RSs in detail, we need to discuss the existing ways of doing this. According to (Yuen et al. 2002), the most used RSs in literature are content-based filtering (CBF), collaborative filtering (CF), knowledge-based filtering (KBF) and their hybridization (combination). CBF tries to guess what a user might like based on that user's activity (more of the same). It makes recommendations by using keywords and features assigned to objects and matching them to a user profile (Javed et al. 2021). CF does not need features of the items to be given (Singh et al. 2020), it is only based on past interactions that have been recorded between users and items. Similar users or similar items can be detected and predictions can be made based on these estimated facts and information (what is popular among my peers). KBF is based on explicit knowledge of the item assortment, user preferences and recommendation criteria (Chen et al. 2019), then reasoning what items will best satisfy the user's requirements (what fits my needs). Finally, hybrid RS is one of the most effective ways to obtain better performance by combining the different types of RS described above. In the next subsections, we rely on these explanations to choose the best method for each RS that we propose.

6.3.1 Peer recommendation

Further to the goal of helping teachers to improve their use of the LMS, we provide them with automatic peer recommendations. Thus, when the teacher obtains low scores in an axis, if there is a close peer with better metric values (exploits more functionalities in their courses) for that axis, the system invites the current user to contact that peer, giving an example of one of their relevant courses so that the teacher can get inspiration from the colleague's course.

In social comparison studies, individuals don't tend to evaluate their opinions and abilities by comparing themselves to people who are too different from them (Litman 2008; Buunk et al. 2012). Consequently, if people avoid comparing themselves to those consid-

ered not close to them, they would also avoid asking them for help. For this reason, peer recommendation should also take into consideration this fact. The concept of similarity on certain dimensions in the context of social comparisons is called dimensional closeness. It has been defined by (Buunk et al. 2012) as “the extent to which individuals perceive the self as close to the comparison target on a specific dimension, such as, intelligence, academic competence or physical attractiveness”. The closeness between teachers in our case can be studied along two dimensions: thematic and physical. While the thematic dimension allows to propose teachers with similar specialties and attached to close teaching departments, the physical dimension considers the location of teachers since our University is spread over two distant sites. Taking these two dimensions into account would enable us to recommend colleagues with related fields, which can help teachers further improve their course environment. Also, by reducing the physical distance between them, the process of asking for help in person would be easier.

On the other hand, our behavioral model is agnostic to the learning domain so far, and thus does not capture the difference of practice that may exist from one discipline to another. We could not include the latter because we did not have enough structured data to study all specialties. However, by recommending close colleagues, we can cover that aspect a bit and improve the probability that teachers benefit from sharing a professional context.

Regarding the technical implementation, we built a hybrid RS combining (i) a CBF to identify close colleagues in order to make it easier for teachers to get in touch, and (ii) a KBF to recommend among them, those with better scores.

To calculate the similarity between teachers, we created a proximity feature that concatenates the site, teaching department, and specialty of each teacher:

$$proximity = \sum_{t=1}^T site_t + department_t + specialty_t \quad (6.3)$$

With T the total number of teachers.

Then, we used the TF-IDF⁵ (Term Frequency-Inverse Document Frequency) technique to vectorize this proximity. It calculates the frequency of appearance of a word in a text, weighted by the number of texts in which it appears. Its aim is to reduce the importance of words that appear frequently in the proximity column and, therefore, prepare the proper format for the similarity calculation. Results of this step yielded a matrix where each

5. https://scikit-learn.org/stable/modules/generated/sklearn.feature_extraction.text.TfidfVectorizer.html

row represents a word in the proximity vocabulary (all words that appear in at least one teacher’s proximity), and each column represents a teacher.

The next step was to calculate the similarity between teachers based on their closeness (proximity feature). To do this, several metrics can be used, such as Manhattan, Euclidean, Pearson, linear kernel and cosine similarity scores. They all gave the same results, so we opted for the linear kernel because it is easy and fast to calculate. The values of the proximity after the calculation of similarities range from 0 to 1. A proximity of 1 between two teachers means that they have the same site, department and the same specialty. Thus, we were able to identify the closest colleagues for each teacher by sorting the similarity scores in a descending order.

The KBF relies on rules allowing to suggest close colleagues with better metric values. In other terms, it aims to relate close teachers to each other based on their usage scores. Thus, it considers the proximity calculated in the previous step, the curiosity score (Cs) and the homogeneity score (Hs). This is done by maximizing the proximity (a higher proximity value between two teachers means that they are closer) and the usage scores (high scores mean that teachers are more familiar with the LMS). Accordingly, we have defined the following 4 priority rules to provide more accurate recommendations:

- The first priority recommends teachers with a high value of proximity (P), curiosity score (Cs) and homogeneity score (Hs), which can improve both teacher usage scores while referring to colleagues who are close. It can be represented by the following formula, close colleagues means that P tends to 1:

$$(Cs_c \geq Cs_t) \wedge (Hs_c \geq Hs_t) \wedge (P \sim 1) \quad (6.4)$$

knowing that, t: teacher, c: colleague

- The second priority aims to recommend teachers with a high value of proximity and one of the metrics, which can improve either the Cs or the Hs, while still recommending close colleagues:

$$((Cs_c > Cs_t) \vee (Hs_c > Hs_t)) \wedge (P \sim 1) \quad (6.5)$$

- The third priority does not consider proximity but aims to improve both usage scores:

$$((Cs_c \geq Cs_t) \wedge (Hs_c \geq Hs_t)) \forall P \quad (6.6)$$

- The fourth priority doesn't consider proximity as well and aims at improving one of the usage scores (Cs or Hs):

$$((Cs_c > Cs_t) \vee (Hs_c > Hs_t)) \forall P \quad (6.7)$$

Sorting teachers by priority (from 1 to 4) allows to get the most interesting and relevant recommendations. For example, figure 6.5 plots colleagues we can recommend to the teacher X for the evaluation axis. This teacher has a curiosity score of 60% and a homogeneity score of 11%. His specialty is “computer science”, his department is “Laval University Institute of Technology”, and he is located (site) in “Laval”. The system recommends teacher A as the closest colleague since he is given first priority (purple color) and the Euclidean distance (d) between them is 42.72, which is the highest (it maximizes proximity and the usage scores). The Euclidean distance is calculated based on the proximity, the curiosity score and the homogeneity score. The closer the proximity is to 1, the closer the colleagues are to each other and the higher the usage score, the more teachers are familiar with the LMS. Therefore, the colleagues to recommend are those with the highest distance between them.

Information of the colleague A shows that he is attached to the same department, thus they are in the same site, but he has a different specialty (electrical engineering) which explains the value of proximity ($p=0.71$). Moreover, he has a curiosity score of 100% and a homogeneity of 26% (both values are higher than those of teacher X). In contrast, the last colleague our RS can recommend in this case is teacher B . He is ranked in the fourth priority (yellow color) with a very low distance value ($d=1.15$). This teacher has almost the same scores as the teacher X ($Cs=60\%$ and $Hs=12\%$). However, the proximity between teacher B and X is 0.4, which is not a very high value. This is mainly due to the fact that teacher B is assigned to another department (Faculty of Science and Technology), they are not on the same site (teacher B is on Le Mans site) but they nevertheless share the same speciality.

To further enrich this RS, we provide with each recommended colleague an example of one of their courses considered as relevant to help the teacher get some inspiration from that course. To this end, we relied on the diversity of exploitation of each axis' features, within each course. Therefore, we calculated the teacher's curiosity score for all their courses, then we chose the one with the highest value, i.e. the course that presents a great diversity in the use of the axis features. The teacher can ask their colleague to

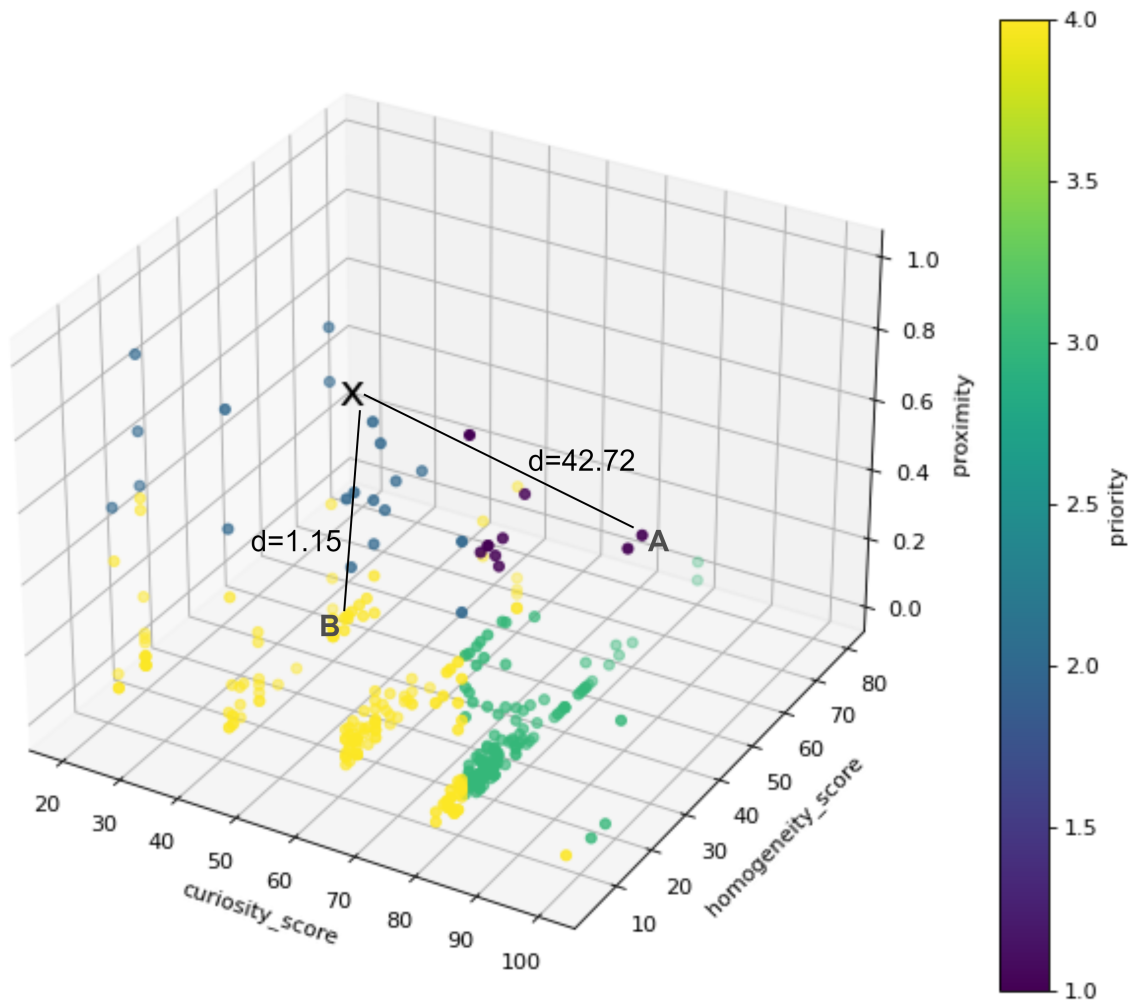


Figure 6.5 – Scatter plot of colleagues to recommend for teacher X on the evaluation axis.

have access to this course in order to check its structure. Then, if the teacher needs to use features or options that he/she don't master, the colleague can help if agreed.

6.3.2 PEs recommendations

Recommendations of PEs simply consist of suggesting the contact of PEs to teachers who need help. Based on a questionnaire sent to teachers to get their needs and preferences on how to improve their use of the LMS (we will detail it in section 7.1). We found that most of them choose to contact PEs if they encounter problems in using the LMS. Therefore, in addition to peer recommendations, we chose to add PEs recommendations. Technically, this RS does not require an analytical method to implement it but only an integration in the application we developed.

6.3.3 Recommendations for unused features

The two previous recommendation systems attempt to exploit the subjective norm to help teachers improve their techno-pedagogical skills. However, we assume that in addition to this social factor, we can also act on personal factors such as improving the teacher's self-efficacy (Cigdem et al. 2015). Therefore, we propose a third RS that aims to suggest all features that are not used by teachers according to each axis. The objective here is to encourage teachers to discover and leverage the various functionalities of the LMS on their own. To do this, we designed a KBF RS based on the curiosity score (Cs) which expresses the diversity of the teacher's use of the each axis functionalities. Thus, for each axis, the system invites the teacher to consider the unused features of the axis that could be useful to improve their teaching practices. The recommended features can be formalized by the following statement:

$$Features = \{i \text{ such as } \sum_{c=1}^{C_t} x_{t,i,c} x_{t,i} = 0 \forall i \in [1, m_a]\} \quad (6.8)$$

With x_t, i, c the value of the feature i_{1,m_a} (m_a the num. of features for the axis a) for the teacher t in the course c_{1,c_t}
 c_t the number of courses where the teacher t has at least one non null variable.

6.4 Synthesis

Leveraging results from both quantitative and qualitative studies, we designed an axis-based model that categorizes teachers' use of the platform to allow them assess their practices along different dimensions (evaluation, reflection, communication, collaboration, resources, interactivity and gamification). From this model, we designed several TA indicators. We proposed The LMS usage trends that enables to distinguish active from non active teachers in a particular axis, as a metric for social awareness. For a more personal self-awareness, we took into account the complete model, including variables that relate unused features so far, into two different scores also proposed by axis. One evaluates the curiosity of the teachers while the other one measures their regularity over the courses they provide. We then proposed 3 recommender systems to help teachers improving their practices in the University LMS: (i) a simple RS to directly ask PEs for help, (ii) a set of unused features that could facilitate teachers' implementation of their courses and also enrich them, finally (iii) a peer recommender system that suggests the most recommended colleagues who are the closest thematically and physically in order to collaborate and ask them for help.

The figure 6.6 explains the way we have exploited the model, the metrics and the recommendations defined above. To provide teachers with self-awareness and support their self-evaluation, we designed the behavioral model which is composed of 6 axes. For each axis, the teacher is provided with an LMS usage trend that allows them to see if they have an intensive or non-intensive use of axis' functionalities, as well as the two usage scores (curiosity and homogeneity scores). Therefore, the first block allows the teacher to engage in a learning process in order to improve their practices in the institutional LMS.

To assist the teacher in this learning process, we provide them with several recommendations. When the teacher scores low or is classified as inactive in an axis, if there is an active peer with better metric values for that axis, the system invites the current user to contact that peer, giving an example of one of their courses selected as relevant example. This allows the teacher to get inspiration from the peer's course and benefit from their help. Furthermore, the system recommends to contact a PE or check features we propose which they don't use, for each axis.

Our approach is also intended for PEs to help them detecting important cases. The different TA metrics we propose will be used to identify teachers with special needs for certain axes, in order to offer them a specific and targeted assistance. Furthermore, PEs

are seeking feedback from teachers considered as experts by our system, in order to benefit from their experience and better organize the tutoring for newcomers.

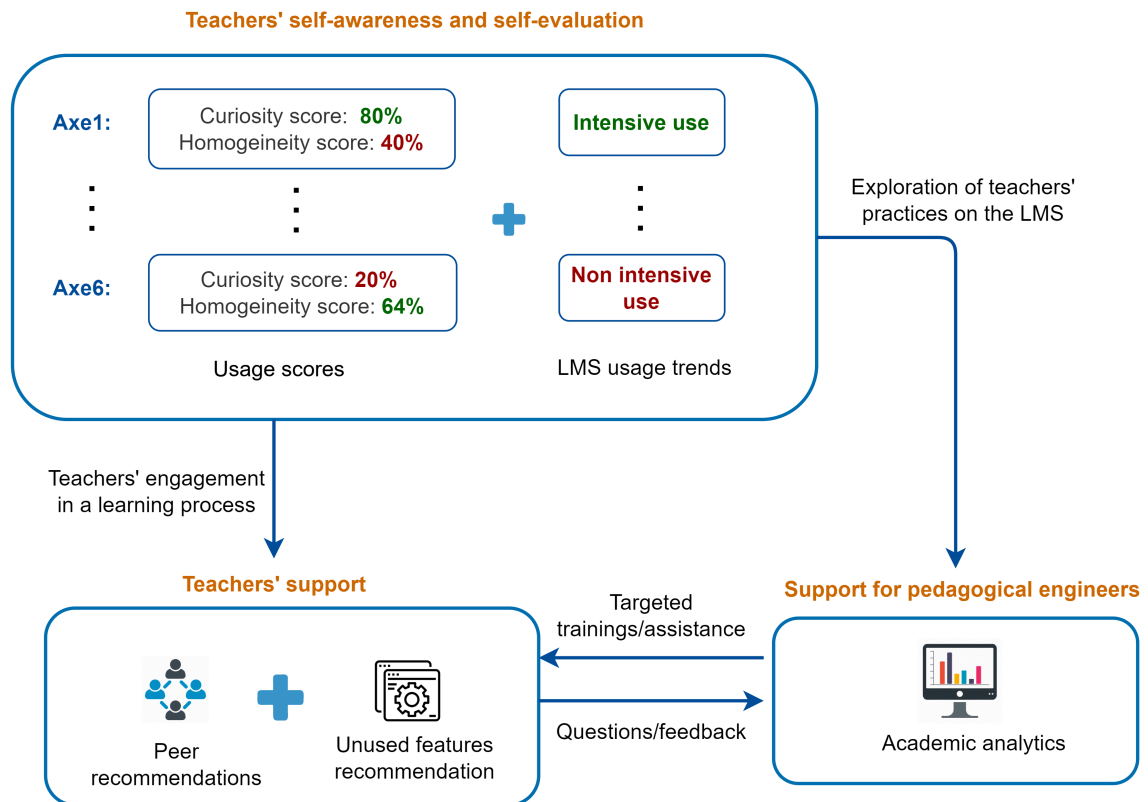


Figure 6.6 – General outline of the approach.

At this stage, we need an application that instruments this approach so that teachers and PEs can test and evaluate it. Therefore, we present this application as well as its experimentation in the next part of this manuscript.

PART III

Application and experimentation

iTEACHAPP APPLICATION

On the basis of the behavioral model, the TA indicators and the RSs we designed, we now attempt to: (i) determine the extent to which teachers understand these proposals and identify their limitations with respect to teachers' own perceptions of LMS use and, (ii) provide teachers and PEs with a digital support tool that best meets their expectations. To do this, we have adopted a user-centered approach that consisted of a questionnaire addressed to teachers as well as three interviews conducted with PEs. Afterwards, we have iterated several times the development of our application named iTeachApp, to leverage the results of the questionnaire and interviews. Thereby, we have reached the visualization phase of our methodology (figure 7.1).

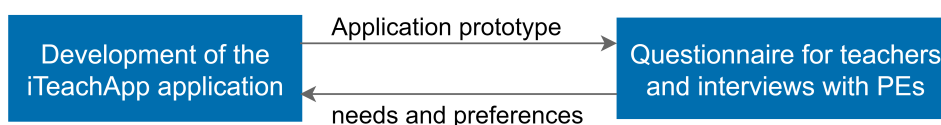


Figure 7.1 – Data visualization stage.

In this chapter, we detail the user-centered approach and its results. Then, we present our application, iTeachApp, through its different interfaces.

7.1 User-centered approach for the model instrumentation

In order to instrument the behavioral model, its TA indicators and the RSs within an application that is more easily accepted by teachers and PEs, we decided to involve them in the design process since they are the end users. Therefore, we elaborated an online questionnaire for teachers and scheduled three interviews with the Digital Resource Center (DRC) directors and the pedagogical engineers of our University (PEs).

7.1.1 Description

The objective of the questionnaire is to validate our proposals (model, indicators, recommendations) and determine whether teachers would be interested in them or not. Furthermore, we wanted to collect their needs and preferences in terms of functionalities in order to develop a more accepted and adopted application.

The questionnaire consists of four sections as presented in the appendix A. The first section focuses on general questions to capture contextual factors that characterize the teacher (university site, gender, age, department and specialty) as well as the number of courses taught and professional experience. The second section aims to distinguish between teachers who are satisfied with using the LMS (Umtice) and those who are not. This was done by using the SUS (system usability scale) questionnaire. It is a standardized survey that includes 10 questions and aims to determine the user's level of satisfaction with a service or a system (Alhadreti 2021). Since teachers' responses may vary according to their satisfaction of the LMS, having this information may be useful to better interpret their responses. For example, teachers who are satisfied with the LMS can give us information about how they use it and what can motivate them to improve their usage. In contrast, dissatisfied teachers can provide explanations about the reasons why they do not use the LMS, the problems they encounter and if there is some way to engage them in using the platform in the future. On the other hand, the third section is devoted to validate the range of features our model covers. While we co-designed the model with PEs, we might have missed particular usage of the platform and wanted here to let teachers check that their practices could be described in our model. In the last section, we aimed to collect teachers' needs and expectations in order to anticipate and make all possible modifications to our application before the experimentation. Thus, in this section, we measure teachers' interest regarding self and social awareness and we investigate what recommendations would be most suitable for them. More specifically, we asked them if they would prefer to seek help from any teacher, a close colleagues, or PEs. Finally, we were interested in knowing if they would be willing to support each other, in order to find out how effective our peer recommendations will be.

Subsequently, we conducted three semi-structured interviews with the DRC (Digital Resource Center) directors and the PEs. The purpose of these interviews was to gather their feedback in order to define and develop the support tool (relying on their experience in dealing with teachers). We chose this type of interview to ensure that interviewees would be free to discuss further hypothesis during the exchange.

The first two interviews were conducted with the head and deputy head of the DRC, one month apart, and lasted approximately 2 hours each. The third interview was conducted with the same individuals plus 5 PEs, and took about 3 hours. During the first interview, we used as a basis for discussion the statistical results of the questionnaire addressed to teachers, together with a first prototype of the application. In the second and third interviews, we proposed a new prototype, taking into account the comments made beforehand, and thus we iterated the development of the application several times.

7.1.2 Findings

Questionnaire

Regarding the questionnaire, we received 76 responses from teachers. The results of the SUS questionnaire allowed us to construct the satisfaction score which ranges from 1 to 100 as shown in figure 7.2. Thus, according to teachers' answers, we have 10 teachers who are not satisfied with the University's LMS (score less than 50), 47 who find the platform quite satisfying (score between 50 and 75) and 19 who showed their high satisfaction with the LMS (score greater than 75). These results indicate a diversity of opinions among correspondents, which provides us with an overview of the participants' usage of the platform and reduces the potential bias of falling into a single category of teachers.

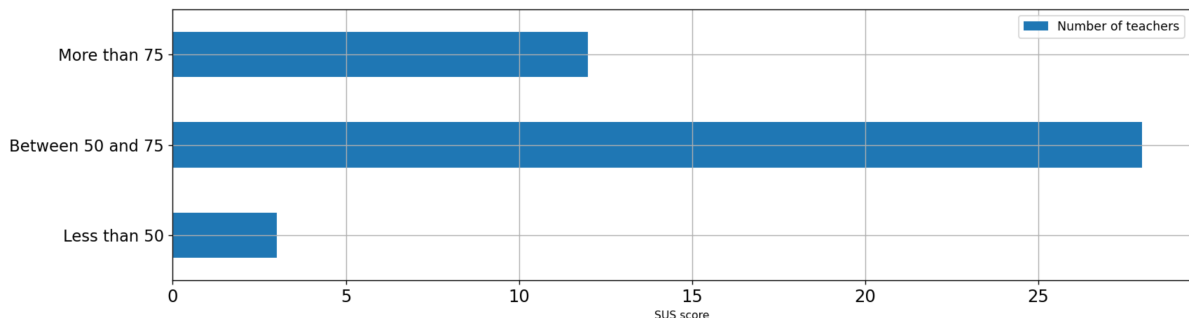


Figure 7.2 – SUS score.

For the use of the platform's functionalities, the figure 7.3 illustrates the results obtained from the likert scale we used. Most teachers (74 respondents represented by dark and light green colors) frequently use the LMS resources. Evaluation features are the second most used feature with 50 respondents using them frequently. In third place, we have communication tools and activities used by the teacher to get feedback from their

students, with 18 and 12 teachers respectively using them frequently. Finally, the least used features are those related to the axes of collaboration and interactivity with 67 and 61 teachers who don't use them at all (represented by the dark and light red colors in the figure). These results validate our previous findings (the fact that Umtice is primarily used as a depository tool and sometimes to evaluate and communicate with students) but this time by considering the opinion of teachers themselves.

Some teachers mentioned using other features: (i) activity reports indicating the number of views for each activity and resource, as well as (ii) the use of “groups” functionality allowing a teacher to form groups of students within a course. With the exception of these two functionalities, we have not identified on the basis of this questionnaire any use of the LMS that is not covered by our model. This model should therefore be enriched to integrate a dimension concerning the management of students, while the existing “reflection” axis will be completed by the functionality of displaying the number of views on a report.

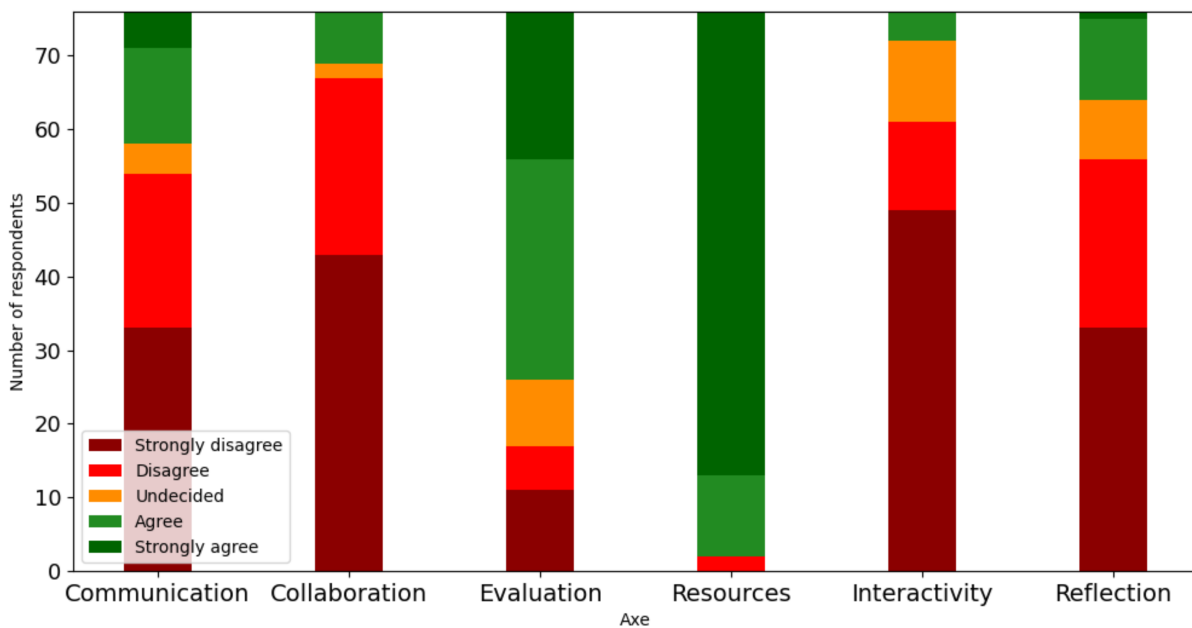


Figure 7.3 – Use of the LMS by teachers.

In the last section, 57 teachers expressed their wish to have a tool for peer recommendations or to get feedback on their use of the platform, and 14 teachers wanted it for self-evaluation. We left the question open to other proposals, so one teacher mentioned

that they preferred training over several times, two other teachers proposed tutorials for certain functionalities or a guide of good practices and what they can do on the LMS. 7 teachers mentioned their unwillingness to get a tool complementary to the University's LMS, probably because they are satisfied with the platform (all have a satisfaction score above 50), so they do not need help. Among teachers seeking help, we received 51 responses, to both choices (i) asking for help from PEs and (ii) from a close colleague. Finally, 65 teachers were willing to help their colleagues if they ask, which is a positive point for our peer RS. Therefore, these responses assess the need to provide a support tool for teachers as a significant portion are interested in having one and many would like to be able to incorporate recommendations from close colleagues and pedagogical engineers.

Interviews

Based on the results of the previous questionnaire, we developed a prototype of our application that was presented during the first interview with the DRC directors, and improved afterwards. The latter provided insights on the need to promote digital trust (what enables individuals to engage online with confidence) (Pietrzak et al. 2021). In our case, this trust implies the need to give the teacher the right to accept or refuse to be recommended to their colleagues. Furthermore, they emphasized the importance of providing teachers with the list of courses we studied and the time interval of each course to ensure that they are aware of the origin of their results. On the other hand, they suggested clarifying some of the terms we used to be more understandable to teachers, for example: the regularity score becomes homogeneity score, and the subtitle "active" used to refer the LMS usage trends indicator becomes "intensive use". Regarding PEs dashboard, they were interested in having a filter by indicator (LMS usage trend, curiosity score and homogeneity score) to better identify teachers in need or those considered as experts by axis. Moreover, they indicated their desire to have a link to see each teacher's dashboard (without having access to their profile page which contains personal data).

7.2 Implementation of the application

7.2.1 Functionalities

Features and options provided by our application can be categorized into 6 main groups as illustrated in figure 7.4.

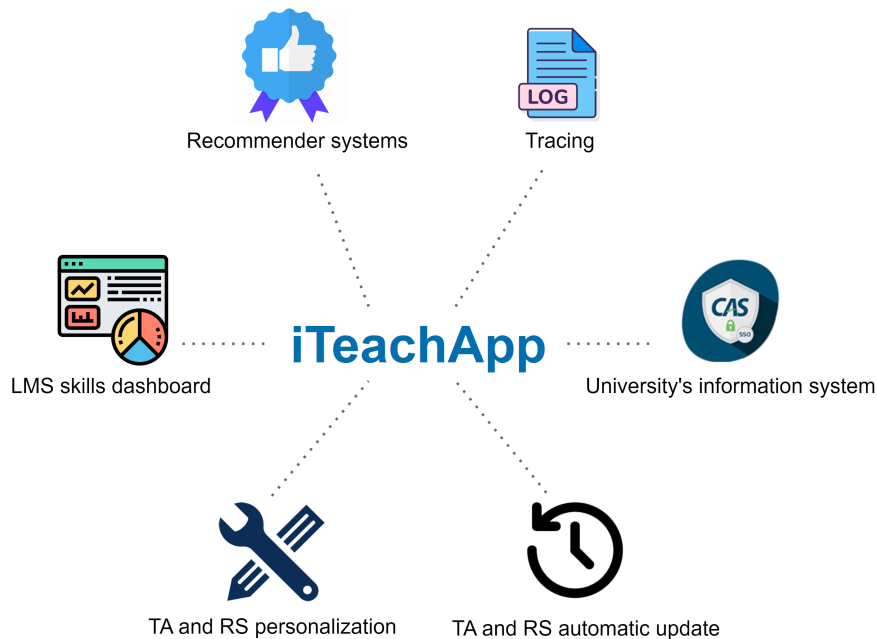


Figure 7.4 – iTeachApp functionalities.

- **University' information system:** our system is also related to the information system of our University. It offers an authentication with the CAS server (Central Authentication Service), which is a unique authentication system for the web. Once a user authenticates to a website, they are then authenticated to all websites that use the same CAS server. Therefore, teachers and pedagogical engineers can use the same credentials to connect to the various platforms of Le Mans University.
- **LMS skills dashboard:** the system provides teachers with a dashboard that allows them to visualize their situation regarding the use of LMS. PEs also have another dashboard that provides an overview of teachers' results using several filters.
- **Recommender systems:** three recommender systems are integrated in our application to help teachers improve their practices in the LMS.
- **TA and RS personalization:** teachers have the possibility to customize their TA and recommendations. They can choose to accept or refuse to be recommended to their colleagues and even set the maximum number of recommendations they can appear in. Moreover, they can select the courses to be taken into account when calculating their indicators.

- **TA and RS automatic update:** the application allows to automatically update scores and recommendations provided to teachers. Each month a script is launched to recalculate the indicators by axis considering the new teachers' activities on Umtice (Moodle). Another script is launched every night to recalculate the recommendations and indicators in order to take into account teachers' choices made by exploiting the features related to the "Profile settings" group.
- **Tracing:** our system allows to track users' activities on iTeachApp in order to perform further usage analysis. Therefore, all the teacher's actions are recorded in log files. To do this, we have defined a model related to several contexts in order to facilitate the trace storage (see appendix C).

7.2.2 Technical architecture

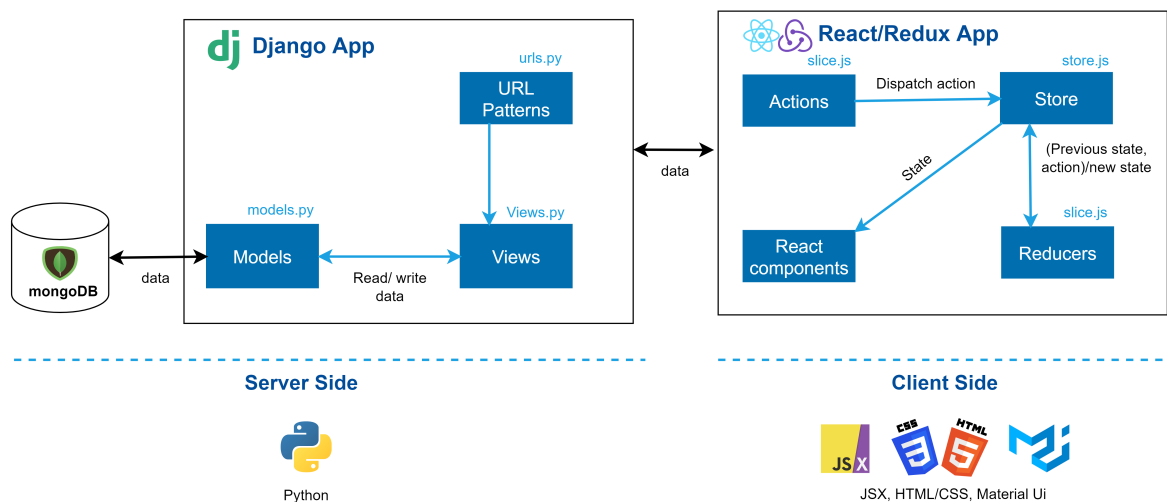


Figure 7.5 – Technical architecture.

The figure 7.5 represents the technical architecture of our application. It describes the various programming languages and technologies used to build it. Thus, we used MongoDB¹ as a document-oriented NoSQL database. This choice was made because it allows to save unstructured data: a need we have since our method require quick and possible adaptation to users' need, especially in the behavior model structure that may vary through time. Moreover, MongoDB provides increased security, reliability and efficiency.

1. <https://www.mongodb.com/fr-fr>

For the back-end development, we used Django² which is a high-level Python web framework. Since we performed the previous data analysis with Python, we chose to use the same language for the development of the web application. Furthermore, Django is rich in pre-implemented functions, offers developers a set of modules and functions such as user authentication, content administration, RSS feeds, etc. It uses the MVT (model-view-template) architecture which is inspired by MVC.

For the front end, we used ReactJs³ which is a free JavaScript library developed by Facebook since 2013. We chose it for its potential to reuse components. It facilitates the creation of single-page web applications, via the creation of components that depend on a state and generate an HTML page (or portion) at each state change. In our architecture, ReactJs is considered as the template part of the MVT model.

React uses Redux⁴ to manage data and the state. It is a light weighted State Management Tool that helps the components in a React App to communicate with each other. It is composed of 3 components: store, actions and reducers.

Finally, to render more attractive interfaces, we have used Material UI⁵. It is an open-source project that features React components implementing Google's Material Design. It includes a comprehensive collection of prebuilt components that are ready for use that's why we exploited it.

7.3 *iTeachApp* application

After we made all the necessary modifications to *iTeachApp*, taking into account the feedback from the DRC directors, we were able to provide a first version ready to be experimented by teachers and PEs. In this section, we present the current version of *iTeachApp* that is deployed at our University.

7.3.1 Teacher's interfaces

Once logged in, teachers can have an overview of their situation as shown in figure 7.6. Each axis is detailed in an accordion with a different background color: green for axes where the teacher has a high tendency to use the platform features represented by the

2. <https://www.djangoproject.com/>

3. <https://fr.reactjs.org/>

4. <https://redux.js.org/>

5. <https://mui.com/>

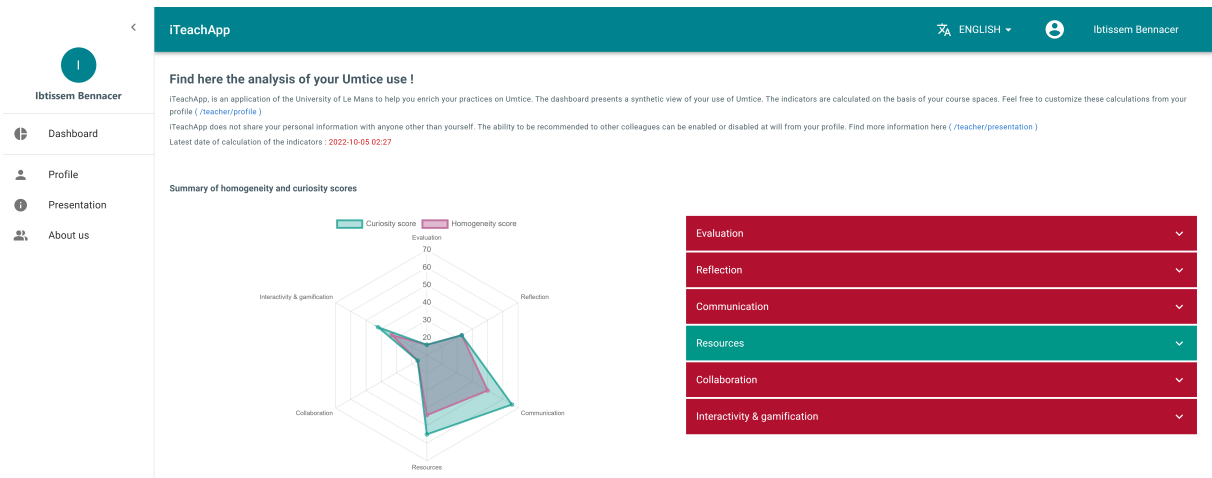


Figure 7.6 – Teacher’s dashboard.

axis in question (intensive use), and red color for the opposite case (non-intensive use). For the example provided in figure 7.6, the teacher has intensive use only on the resource axis (green color).

For each tab, teachers visualize the same information as shown in the figure 7.7. The two different curiosity and homogeneity scores are included as well as a the LMS usage trends indicator. Axes and scores are also provided with help messages for the teacher to (i) understand its overall signification through a simple vocabulary (e.g. the LMS features involved in the axes), and (ii) a more formal definition for those who seek for a precise definition (e.g. the mathematical definition of the score) in the presentation page. Moreover, each text was reviewed with PEs to avoid any ambiguity or any misinterpretation regarding the meaning of the different TA indicators or axes. For instance, we avoided any term that might imply a judgment of the teacher, such as “inactive teacher”.

Furthermore, We have integrated the recommender systems discussed in section 6.3 into *iTeachApp* application. They are displayed below the TA indicators in the same figure 7.7. For this example of the “Evaluation” axis, the teacher can visualize: (i) a set of unused features that might help them to facilitate the evaluation of their students, (ii) the “Contact a Pedagogical engineer” button which opens an email box to directly contact PEs with a pre-formatted email indicating the name of the axis and the scores obtained as depicted in the figure 7.8, and finally (iii) the “Ask a close colleague” button which opens the window presented in figure 7.9. It displays the top 3 most recommended colleagues. We have chosen to recommend 3 colleagues in order to allow the teacher to choose whom

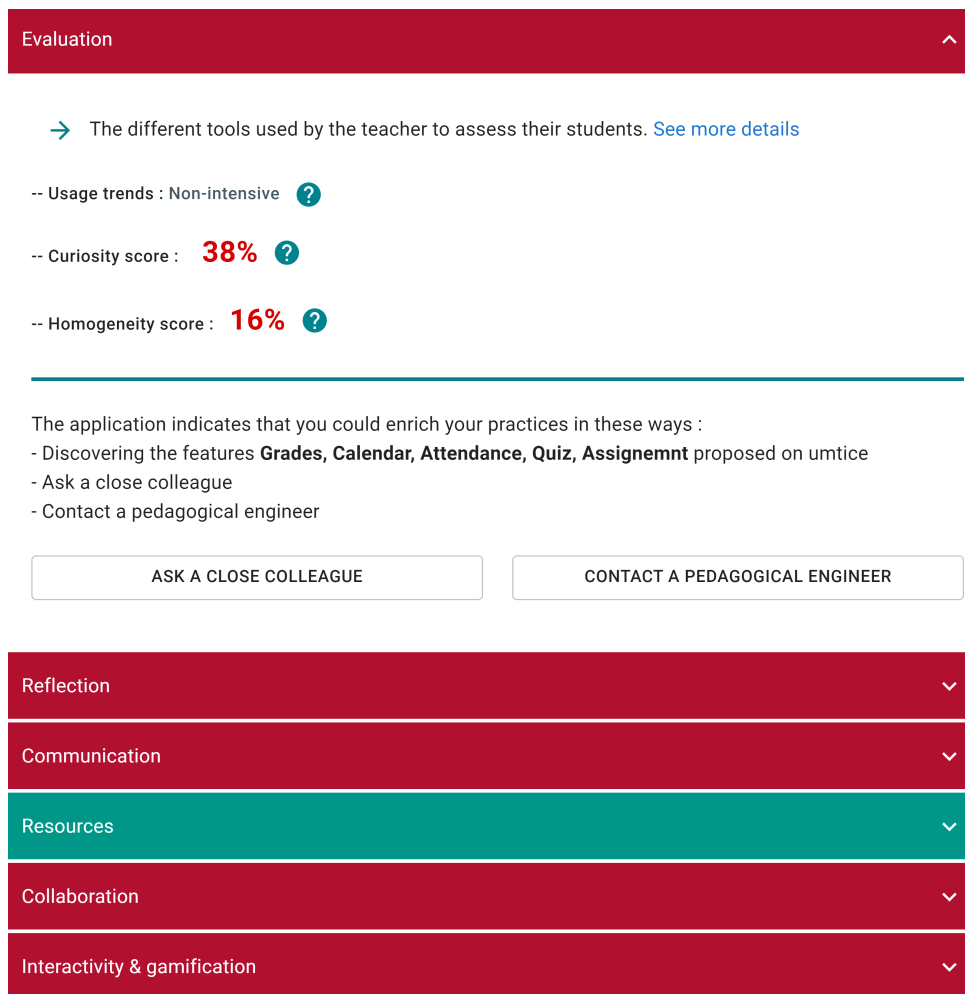


Figure 7.7 – Details of the evaluation axis tab.

to contact but, at the same time, if one of them does not respond positively, the teacher can contact another one. For each colleague, an example of one of their courses selected as relevant for that specific axis is given with a description of the course on mouse over. To contact a colleague, a click on their names opens an e-mail box for this purpose and to consult their information, a simple click on “See more information about the teacher” displays their title, specialty and department. Such information can help the teacher to choose whom to ask for help and find them more quickly.

On the left of the accordion detailing the axes, we provide a radar visualization that summarizes both scores so that the teacher can have a comparative view of the different axes (see 7.10). This type of visualization is chosen because radars are useful for seeing

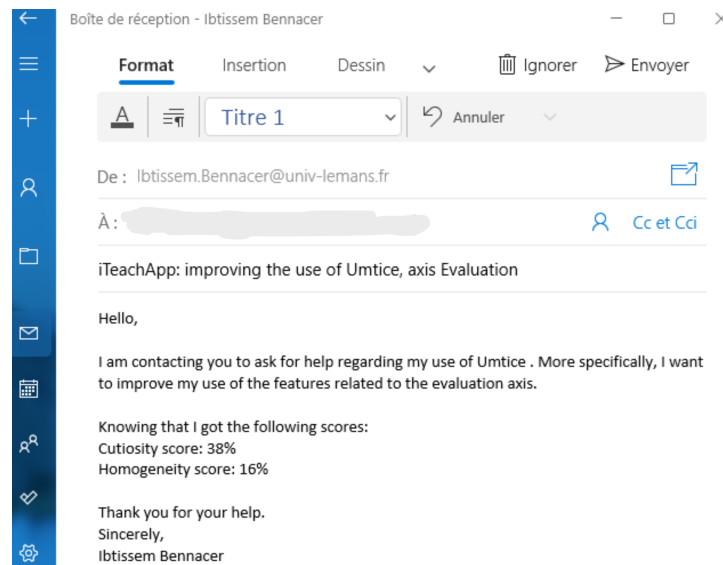


Figure 7.8 – Contact PE.

which variables score high or low and thus they are ideal for displaying performances. Therefore, it allows teachers to easily picture how they use the institutional LMS and also to position themselves on what they want and prefer to improve in their mastery. In the example provided, we can see that the teacher’s practice is based on the use of communication tools and resources. The other axes are not well explored, especially the functionalities that promote collaboration between students. The teacher can therefore position themselves and choose the axes on which they want to act.

Figure 7.11 shows the teacher’s profile interface. This page was added mainly to allow teachers to customize their recommendations and adjust the calculation of their indicators. On part **A**, teachers can view their personal information (username, email, title, specialty and service). On section **B**, teachers can accept or refuse to be recommended to colleagues who need help using the provided switch. This option allows to ensure the promotion of the digital trust requested by the DRC. Moreover, they can choose the maximum number of recommendations per month in which they can appear, by default, each teacher can be recommended to a maximum of 3 colleagues per month. We decided to add this setting to not burden teachers and give them the possibility to decide how many colleague they want to help according to their availability.

On part **C**, we display a table of the teacher’s courses that were used to obtain their indicators and recommendations, with a link to each one in the institutional LMS (Umtice).

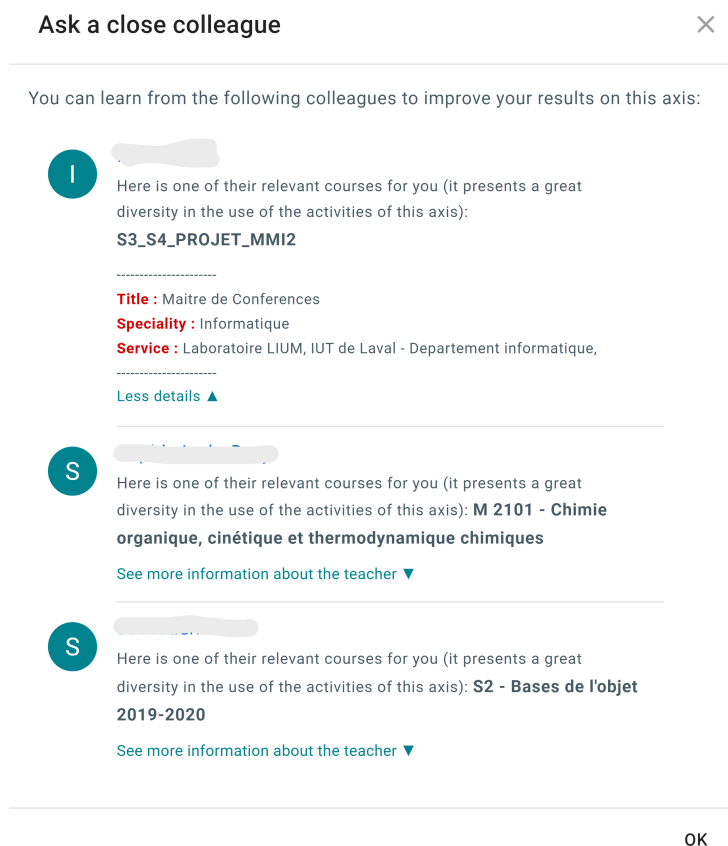


Figure 7.9 – Peer recommendation in iTeachApp.

For each course, we specify the name, description, scholar year, and give the teacher the option to keep or remove each course from the next indicator calculation. This last option concerns teachers who create courses with their credentials for their colleagues when the course is not their own or for courses' environment used to manage administrative processes. Our purpose here is: (i) to correct the automatic calculation of teachers' metrics as well as the analysis of their practices, by removing noise, and (ii) to improve the digital trust by giving users the ability to monitor how the system analyzes their behavior.

7.3.2 Pedagogical engineers' dashboard

iTeachApp is also addressed to PEs to help them detect cases of importance. The figure 7.12 represents the PE's dashboard. At the top of the page (part **A**), a data table is provided to visualize the list of teachers with their information (name, first name, service

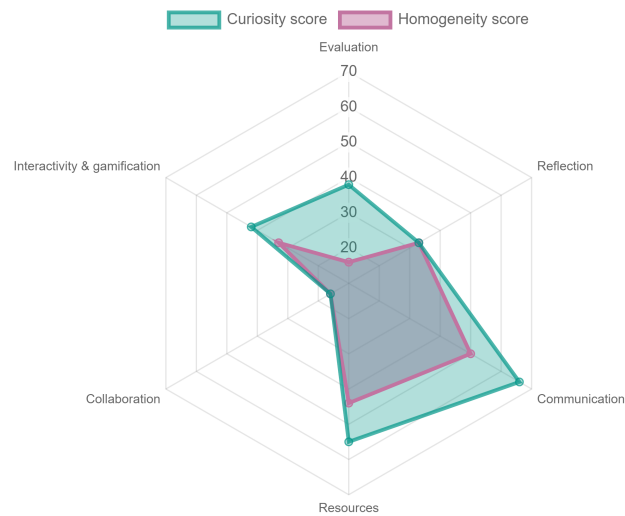


Figure 7.10 – Summary of homogeneity and curiosity scores.

A

Ibtissem Bennacer

Username : ibenna
 Email : Ibtissem.Bennacer@univ-lemans.fr
 Title : Contractuel Doctorant
 Speciality : Informatique
 Service : Laboratoire LIUM

B

Do you accept to be recommended to your colleagues who would like to improve their skills on Umilce ?

We can recommend you to your colleagues (they can contact you by e-mail to ask for your help)

The maximum number of colleagues to whom we can recommend you per month :

5

C

Course	Description	Scholar year	Considered in the current calculation of the indicators?	Take into account the next calculation of my indicators
M3202 Développement web S3	Le but de ce module est d'approfondir le développement PHP en construisant progressivement une application de gestion de « tâches à effectuer » reposant sur une architecture MVC et utilisant la réécriture d'URL. Cette application mettra en œuvre une architecture générique, réutilisable et extensible permettant également d'illustrer le concept de « framework ».	2021	No	<input type="checkbox"/>
R113 - Développement Web	Ressources pour l'enseignement en algorithmique en 1ère année (CM/TD/TP) au département Services et Réseaux de Communication. L'objectif est d'initier l'étudiant à la notion d'algorithme : cycle de vie d'un programme, variable, instructions conditionnelles, boucles, initiation aux fonctions	2020	No	<input type="checkbox"/>
R113 - Développement Web	Ressources pour l'enseignement en algorithmique en 1ère année (CM/TD/TP) au département Services et Réseaux de Communication. L'objectif est d'initier l'étudiant à la notion d'algorithme : cycle de vie d'un programme, variable, instructions conditionnelles, boucles, initiation aux fonctions	2021	Yes	<input checked="" type="checkbox"/>
S1 - Base de l'algorithmique	Ressources pour l'enseignement en algorithmique en 1ère année (CM/TD/TP) au département Services et Réseaux de Communication. L'objectif est d'initier l'étudiant à la notion d'algorithme : cycle de vie d'un programme, variable, instructions conditionnelles, boucles, initiation aux fonctions	2019	Yes	<input checked="" type="checkbox"/>
S2_PROJET_MMII	Gestion des projets de première année du DUT MMI.	2019	Yes	<input checked="" type="checkbox"/>

Rows per page: 5 | 1 - 5 of 6

Figure 7.11 – Teacher's profile page.

and specialty). In addition, the three TA indicators are displayed by axis for each teacher and their dashboards are accessible by clicking on the icon next to the “Axis/Score”

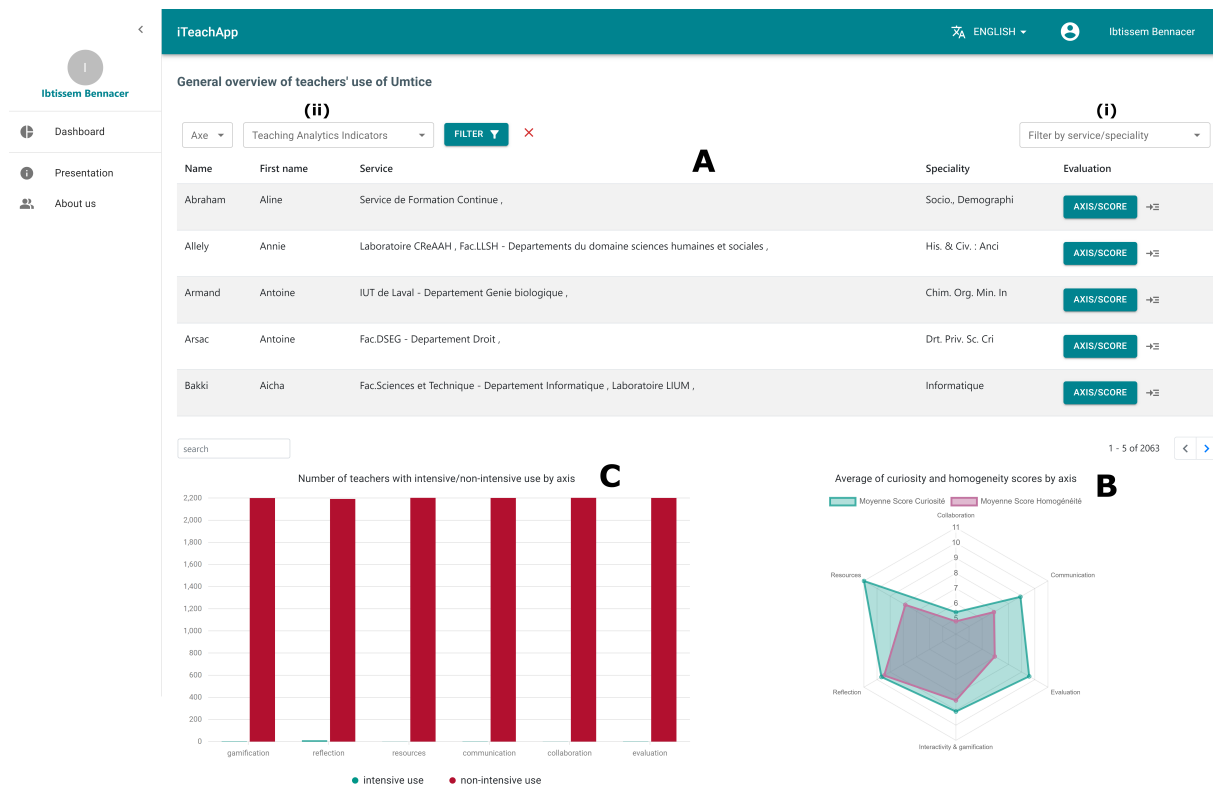


Figure 7.12 – PE’s dashboard.

button. This can help PEs to search for a specific teacher in order to find out about their situation and then to offer them personalized assistance.

To have a global view of these indicators, we provide a radar visualization (part B) that shows the average of the curiosity and homogeneity scores by axis. This may help PEs to better understand the LMS use by all teachers. As we can see, the overall use of Umtime is oriented towards resources with less interest in collaboration. On part C, a bar chart summarizes the average number of teachers with intensive/non-intensive use by axis as well (very few active teachers). On the other hand, our application allows to identify particular users or structures such as teachers in need of help or those considered as experts in order to benefit from their experience. Therefore, we provide PEs with two filters placed at the top of the page. The first (part (i)) enables PEs to select teachers according to their specialties or departments to which they are assigned, which makes it easier for them to compare specialties and detect very active departments, etc. The second one (part (ii)) filters teachers according to their metric values by axis. For example, the

choice of the indicator “LMS trend usage” with the value “intensive use” and the axis “Communication” allows to identify all teachers of the University who frequently use the communication tools of the institutional LMS. PEs can also filter teachers with low scores in each axis. The different TA metrics we propose can thereby be used to detect teachers in particular needs for certain axes, in order to propose them consistent and precise help. In contrast, expert teachers in particular domains of competencies can also be identified. This was a function PEs were looking for to obtain precise feedback from these expert teachers, within the aim of defining factors related to their evolution and also to better organize tutoring for newcomers.

7.4 Synthesis

In this chapter, we followed a user-centered method (i) to validate our proposals (model, TA indicators and RSs) from the teachers’ point of view, and (ii) to identify the best way to provide teachers and PEs with relevant teaching analytics in order to help them improve their skills and meet their teaching needs. For this purpose, we addressed a questionnaire to teachers and conducted three interviews with PEs.

Given the results we obtained from the questionnaire, we discovered that the behavioral model could be enriched by integrating a dimension concerning student management, while the existing “reflection” axis could be completed with a report functionality that we did not detect previously. Regarding teachers’ expectations, we noticed a great interest on their part to have a support tool that provides recommendations from close colleagues and PEs. The majority of them were also open to help each other and to improve their practices on the LMS.

Considering these results together with those from PEs interviews, we were able to select wise types of visualizations and recommendations to provide to teachers within an application that is designed to ensure a digital trust and offer analytics with a proper degree of explainability.

In this chapter, we have also described the different interfaces of our application, which is now deployed at our University. With an operational version of iTeachApp, an experimentation is now required in order to study how teachers would use and appropriate it. The experimentation we conducted will be described in the next chapter.

iTEACHAPP EXPERIMENTATION

Our next step is to experiment iTeachApp in order to investigate its usability and use by teachers. This represents the data action phase of our methodology (figure 8.1) which allows teachers to take actions in order to improve their practices and to provides researchers with insights on how to improve their work.

In this chapter, we present the experimentation we conducted with teachers of Le Mans university providing details of the protocol we followed and the results obtained from the quantitative and qualitative studies.

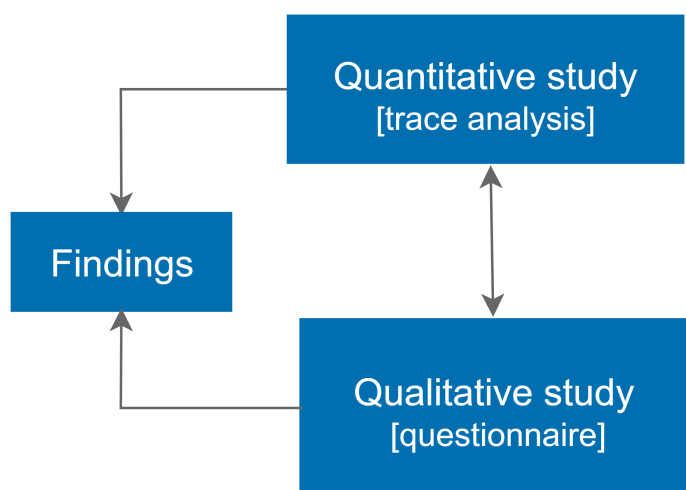


Figure 8.1 – Data action phase.

8.1 Experimental protocol

8.1.1 Description

This experimentation focuses on the use of iTeachApp by teachers and aims to :

- Study the usability (see section 2.2), the utility¹ of iTeachApp and its use by teachers.
- Determine if this application allows teachers to discover new Umtice functionalities and if peer recommendations are effective (i.e. if teachers actually follow up on the recommendation by contacting their peers).
- Eventually improve the behavioral model and its indicators by identifying missed features or axes.

Before starting the experimentation, we followed the next main steps in order to launch iTeachApp at our university :

1. Defining the experimental protocol and validate it by PEs.
2. Performing a GDPR (General Data Protection Regulation) declaration which allows to regulate the processing of personal data within the European Union.
3. Presenting the project to vice-presidents of the university in order to get the validation to launch it.
4. Creating a showcase website² including a video that aims to introduce the project to teachers.
5. Collecting the list of teachers willing to participate in the experimentation.

The participants to this experimentation were teachers using the “Umtice - Sciences Technologies Health (STH)” platform. We only chose the STH specialties because, during the COVID period and due to the buildup in operations, Umtice was split into two platforms: (i) Sciences Technologies Health (STH) and (ii) Humanities and Social Sciences - Law, Economics and Management. However, we were able to recover only traces from the first platform (Umtice-STH).

On the other hand, experimenters were the LIUM researchers who are leading the different phases of this project, as well as the DRC (Digital Resource Center) who were involved in the collection of feedback from teachers contacting them directly.

1. The ability of a tool to meet user expectations.
2. <http://rech-iksal.iut-laval.univ-lemans.fr/iteachapp/>

8.1.2 Methodology

We have adopted a mixed approach to achieve our objectives through qualitative and quantitative studies. A first quantitative analysis aimed at analyzing traces of iTeachApp in order to observe how teachers have actually used the application and adopted its various features. A second process aimed at collecting participants' feedback on the application through a questionnaire, in order to have a more in-depth analysis and to validate the results of the first study using teachers' declarative responses to the questionnaire.

Trace analysis

The current version of our application allows to record what teachers really do on it through its tracing functionality. Thus, to better evaluate iTeachApp, we aim at calculating the following indicators :

- The number of logins to the application.
- The average scores of participants.
- The number of participants with intensive use per axis.
- The most frequently consulted axis.
- The most viewed indicators description.
- The number of recommendations consulted (colleagues/PEs).
- The percentage of teachers who have accepted to be recommended to their colleagues.
- The average value chosen by teachers as the maximum number of colleagues to whom they can be recommended.

Questionnaire

The questionnaire is composed of 4 sections intended to gather feedback from all the teachers who participated in the experimentation (see appendix B). The first section focuses on the general questions about teachers to define contextual factors (age, gender, etc.). The second one discusses the utility of iTeachApp to investigate whether the axes are representative of teachers' activities and whether the TA indicators and recommendations are relevant. Section three explores the usability of our application, allowing to evaluate users' satisfaction, iTeachApp interfaces, the choice of visualizations and texts. Finally,

the last section is devoted to study the use of our application by teachers. In other words, we aim here to identify their different use cases (most consulted axes, most used functionalities, etc.) as well as problems encountered by them and their suggestions to improve the application.

The results of this questionnaire were also analyzed statistically in order to (i) identify different profiles of iTeachApp use, (ii) classify the difficulties encountered by the teachers and (iii) determine possible improvements that could be brought to the application.

8.2 Findings

29 teachers participated to our experiment and thus used the platform and may have been recommended to others participants. This number is considered low but justified by the fact that we launched the project in a very busy period for teachers (start of school year). We also had withdrawals for the next steps due to the same reason. Some teachers contacted us and apologized since they were motivated to participate but did not have enough time to do it. Therefore, we just took these participants and gave them access to iTeachApp for 20 days. Afterwards, we sent them the usability questionnaire and started to analyze their traces.

8.2.1 Quantitative study

The second phase of our experimentation consisted of giving teachers who agreed to participate, an access to iTeachApp in order to test it. Among the 29 teachers who wanted to participate, 21 of them really did. We recorded 39 logins to our application, which means that some teachers visited it multiple times. Since iTeachApp allows to track all actions performed by teachers on the app, we were able to analyze how they really appropriated it.

Before going further into the study of teacher use of iTeachApp, it is necessary to have some background information about the participants in order to better interpret the analysis' results. To do this, we first explored the different specialties of participants as the figure 8.2 reveals. We note that most of our participants were computer scientists (11 teachers) with 2 English teachers and 8 other specialties represented by a single teacher such as physics-chemistry and biochemistry-biology. The specialties were retrieved from the university's directory and stored in our database. Therefore, we do not distinguish, for

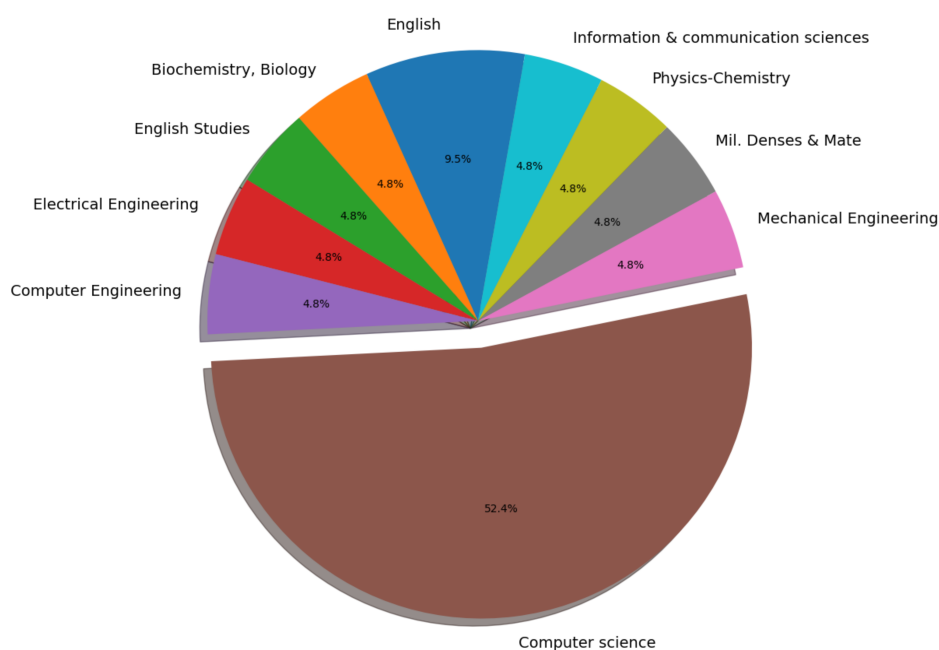


Figure 8.2 – Participants' main specialty.

example, between computer science and computer engineering. The fact that we have a lot of computer scientists may bias our results because this evaluation of iTeachApp will be done mainly by them. In addition, we explored participants' situation regarding their use of the LMS by studying their TA indicators. For the two usage scores, their values on all axes are shown in figure 8.3 which provides an overview of these scores. We notice that the curiosity score ranges from 0 to 100% with rather average values. This indicates that participants cover several cases (teachers with high and low values), which could enable us to study the usability of iTeachApp from several angles. On the other hand, the homogeneity score ranges from 0 to 66% with lower values. Since we have already found that all teachers in our University have low values regarding to the homogeneity score (section 6.2), these results do not have too much impact on our study.

We then tried to see how these scores are spread over each axis. Therefore, figure 8.4 illustrates the average scores of participants by axis. The best curiosity scores are obtained for the axes : evaluation, communication and resources with averages of 41%, 40% and 38% respectively. For the homogeneity score, we have much more homogeneous participants in the reflection axis (the average score is 27%). Then, the remaining axes

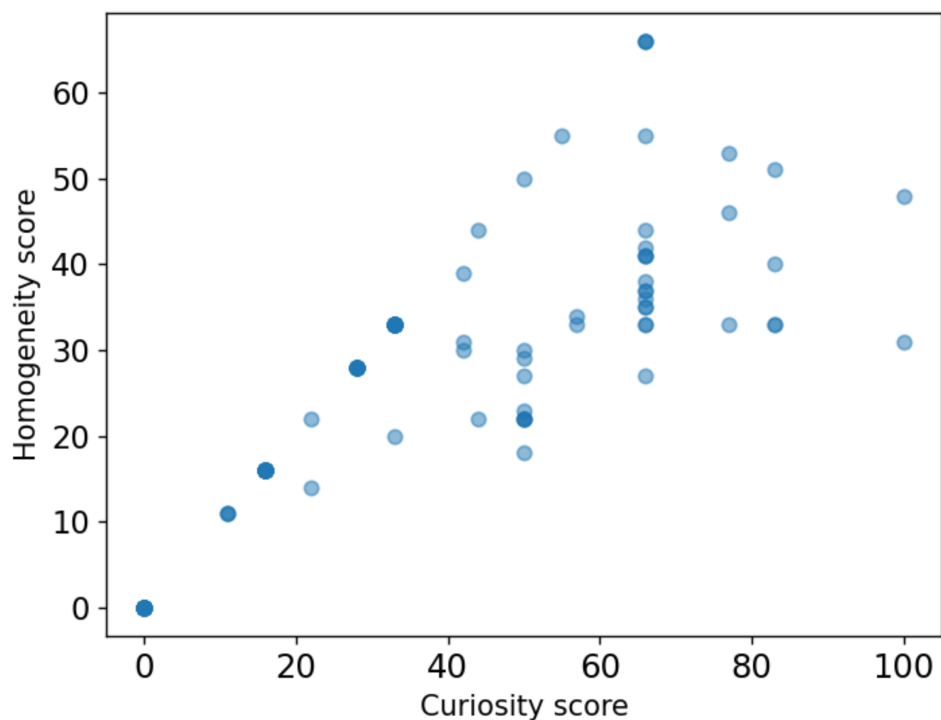


Figure 8.3 – Participants’ score values on all axes.

have the same ranking as the curiosity score. These results are consistent with those of all teachers studied in section 6.2, thus proving that our sample is valid and representative.

For our last TA indicator, the LMS usage trends, we identified only one teacher with intensive use in the reflection axis. This result does not affect us because, in terms of the total number of university teachers, there are only 21 with intensive use on a certain axes.

Afterwards, we investigated how teachers adopted the different axes of our model by comparing their consultations of each axis. The goal was to find out if teachers had preferences for certain axes or not. A frequent consultation of particular axes means that teachers check their recommendations to improve their skills related to those axes. Figure 8.5 presents the results we obtained.

It seems that teachers have a great interest in the evaluation and reflection axis with 51 and 48 consultations respectively. However, this may be due to the fact that the evaluation and reflection axes are displayed before the others in *iTeachApp*. While there is no particular semantic order between axes, the application provides the same presentation for all users. This hypothesis tends to be confirmed according to the distribution of consultations for each axis as shown in figure 8.5 (axes are presented in the same order as in the

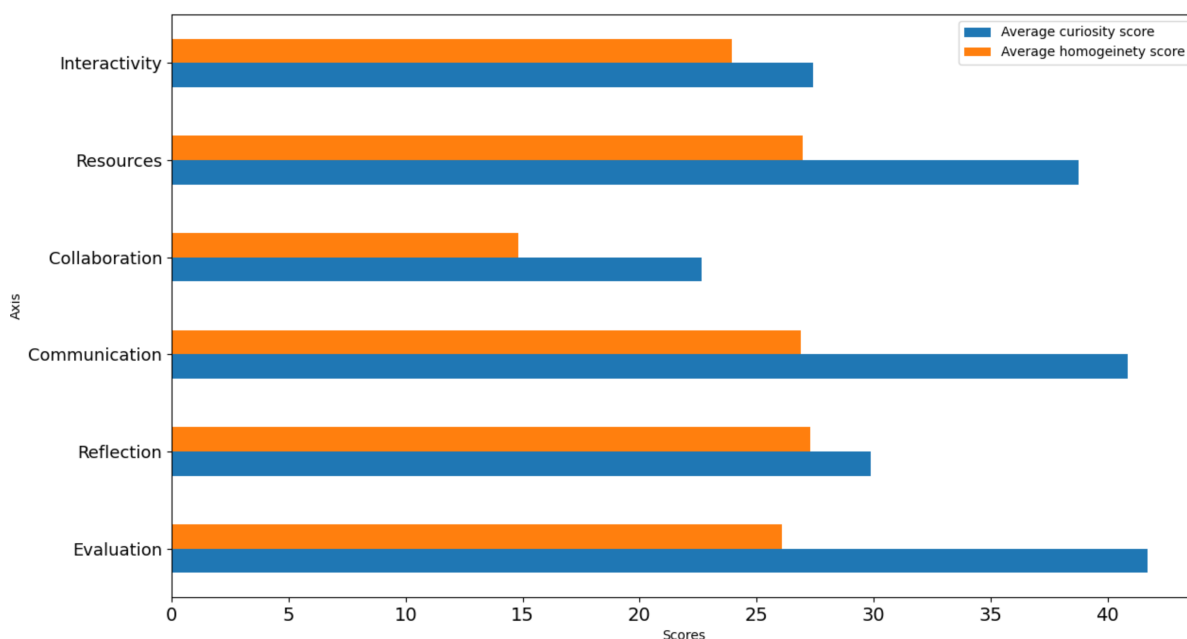


Figure 8.4 – Participants' average scores by axes.

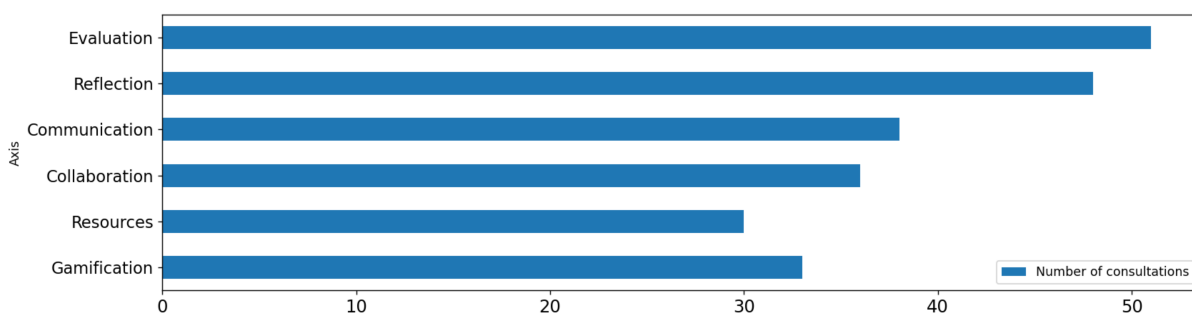


Figure 8.5 – Number of consultations of each axis by teachers.

application). In contrast, the resources axis was considered to be the least consulted axis even though it appears in fourth position in iTeachApp (not last). A possible explanation is that teachers are already using many features related to this axis, thus they are more interested in other axes which might not be familiar to them.

Regarding the use of our TA indicators by teachers, we could not obtain this information from log files because these indicators are accessible without any manipulation by the teacher (we cannot record their consultations). However, teachers can view the description of each axis by clicking on an icon next to each one to get more information about it.

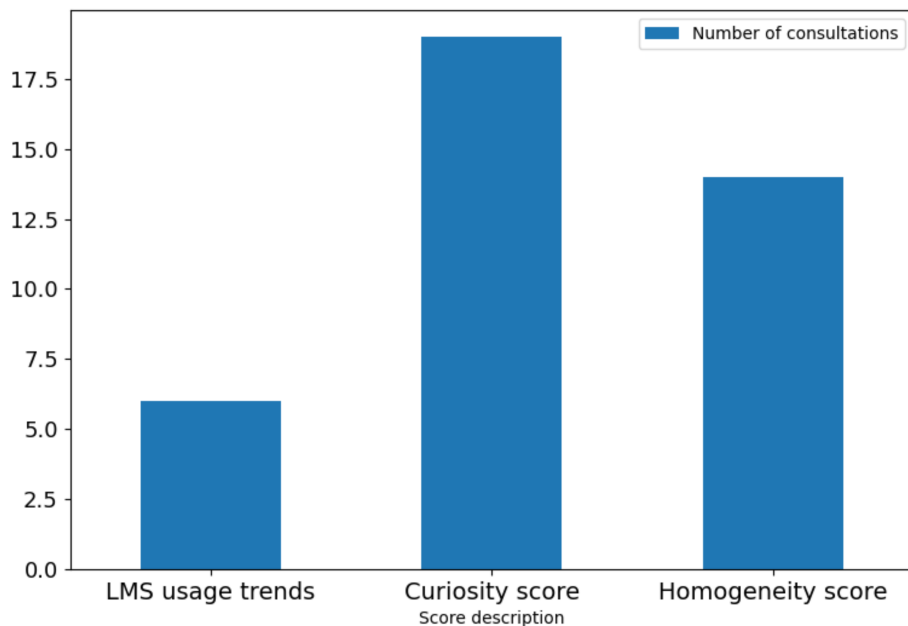


Figure 8.6 – Number of consultations of each TA indicator description.

Therefore, we were able to quantify these actions and identify the most frequently seen descriptions as shown in figure 8.6. The results showed that the curiosity score description is the most consulted by teachers, followed by that of the homogeneity score and finally that of the LMS usage trends with 19, 14 and 6 views respectively. This may mean that teachers are more interested in curiosity and homogeneity scores, that's why they referred to their descriptions for more precision. However, it could also mean that teachers did not understand the meaning of these indicators and therefore the LMS usage trend can be considered as the most understandable indicator for them. This hypothesis should be taken into account because it is confirmed by the questionnaire results that are presented afterwards.

Within *iTeachApp*, we have integrated 3 RSs: unused LMS features RS, peer RS, and PEs RS. It is also worthwhile to study how teachers have used them in order to define their relevance. Since all unused features can be viewed by accessing each axis directly, we could not identify how many times teachers checked them. However, for the two remaining RSs, we were able to compare teachers' consultations based on the number of times they clicked on buttons related to each RS. The figure 8.7 compares consultations of the peer RS to those of the PEs RS. Findings indicated that among all recommendation-related

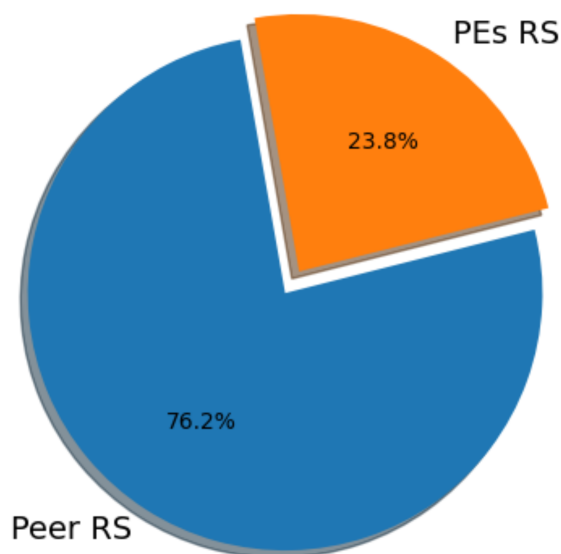


Figure 8.7 – Number of RSs consultations.

consultations, 76.2% (48 views) are related to peer RS, while the rest (15 views) are related to PEs RS. We can deduce that teachers may ask for help from their colleagues more often than PEs. However, it is still possible that they simply consulted these recommendations out of curiosity. The suggested colleagues for each axis may not be the same whereas for the PEs it's always the same contact whatever the axis.

In terms of personalizing recommendations, we calculated the percentage of teachers who accepted to be recommended to their colleagues. It should be mentioned that 18 teachers have really consulted the profile page and left at least a trace on it. The results were very motivating, with all these teachers agreeing (all participants who checked the settings) to be recommended to their colleagues. This allows us to enrich our recommendations because, if few of them accept, the system will not be able to suggest close colleagues to all teachers. Moreover, it proves that teachers are really willing to help each other. Furthermore, we studied teachers' choices regarding the maximum number of colleagues to whom they can be recommended. We found that almost all of them kept the default values (3 colleagues per month) and only one teacher changed it to 2 colleagues per month. This means that our choice of the default value did not disturb most of participants.

This quantitative analysis enabled us to have information about our participants and an overview of how they are using iTeachApp. However, it is limited in terms of information. We cannot track what the teacher mostly views as indicators and recommendations

of features. Moreover, for each use case, we have several interpretations and sometimes not even one. To complete this study, we performed a qualitative analysis in order to collect teachers' opinion directly. This analysis will be explained in the next section.

8.2.2 Qualitative study

The questionnaire aims to deepen our evaluation of iTeachApp and to help us better understand the results of the first analysis. We received 15 responses, which means that among those teachers who tested the application, 6 did not answer the questionnaire. We recently received emails from 3 teachers indicating that they were very busy to finish the experimentation and fill out the questionnaire, but they will be interested in participating in future experiments. 10 of our respondents were computer scientists while the remaining ones had the following specialties: English, Biochemistry-biology, Information and communication sciences, Physics-Chemistry, Electrical Engineering. This follows the same uneven distribution as for the questionnaire. While it may also eliminate some use cases that these teachers do not cover, it tends to highlight the common observation that TEL is first used by scientific teachers, and more precisely the computer science ones.

Regarding our model, TA indicators and RSs, most teachers found them interesting. 9 of the 15 respondents find the representation of their activities by axis relevant. Among those who answered negatively, one teacher specified that she did not have sufficient data to answer the question (indicators and recommendations were not defined). Indeed, she has two courses on Umtice but she is not the main teacher. By analyzing her case, we found out that she never participated in the creation of these courses, and therefore she has no traces that would allow us to investigate her use of Umtice. Furthermore, two other teachers claimed that terms in each axis are not always explicit such as the reflection axis name. As a matter of fact, the label used to represent tools used by teachers to get feedback on their teaching was not understandable. Thus, some teachers were unable to determine the relevance of the axes because they did not understand the meaning of certain ones. Although most of these terms are well known and defined in pedagogy, observations show that we made the wrong assumption about teachers' pedagogical and theoretical knowledge during the design process.

Afterwards, we questioned whether the six axes correctly represent their use of Umtice. All teachers agreed on the fact that axes accurately depicts their use of the LMS, with the exception of the teacher who had no data. This means that, according to respondents, we have not missed some axes or features related to their use of Umtice. Regarding

the relevance of our TA indicators, 11 respondents found them useful for enhancing their practices on Umtice. However, the remaining 4 teachers had problems to understand these indicators, especially the homogeneity score. One stated, “I find the term ‘homogeneity’ unclear with respect to its definition”. The lack of understanding of these indicators leads to a misinterpretation of the results and, therefore, it is important to address this issue. While we spent time selecting terms with PEs, these results highlight a limitation of our methodology. Specifically, we need to involve a more representative panel of experts and teachers in our design process to avoid such problems.

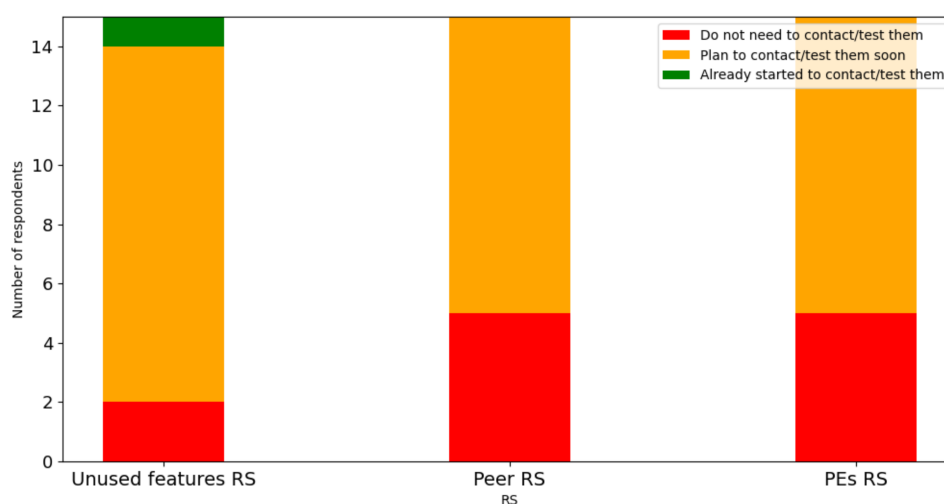


Figure 8.8 – RSs use by respondents.

On the other hand, 12 over 15 respondents found the recommendations motivating to enrich their practices on Umtice, one teacher said “it helps to take a step back regarding the use of Umtice and therefore allows to have a reflection about possible evolution”. While one teacher of the three who did not respond positively said, “my answer is between yes and no. It helps to remind me that there are tools that I use little or not at all. However, not all unused tools are necessarily relevant or we can also use others ‘outside’ of Umtice which are better during our interventions”, the other two respondents wanted descriptions of features and their potential contribution in terms of pedagogy or simply training. Finally, we wanted to see how teachers have used the different RSs so far. Figure 8.8 shows that for the unused features RS, 2 respondents did not feel the need to use them, 12 plan to use them soon or if needed, and one respondent has already started to discover them. For the two social RSs, we received the same results : 5 teachers were not

interested in using them and 10 plan to contact their colleagues or PEs if needed. This part of our questionnaire indicates that most participants find our proposals relevant for them. However, we detected some possible improvement to meet the needs of the remaining teachers. Specifically by (i) identifying more meaningful terms to represent the axes and indicators and (ii) adding descriptions to the features we propose.

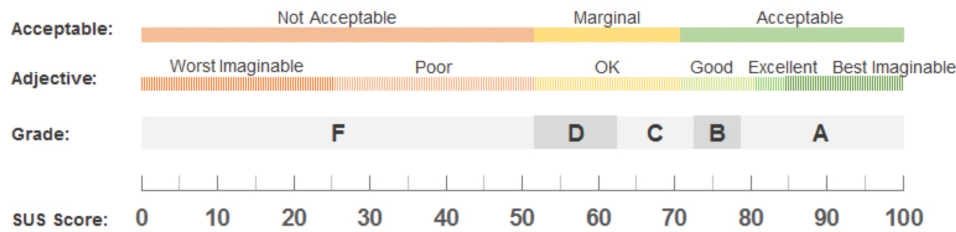


Figure 8.9 – Grades, adjectives, and acceptability categories related to SUS scores³.

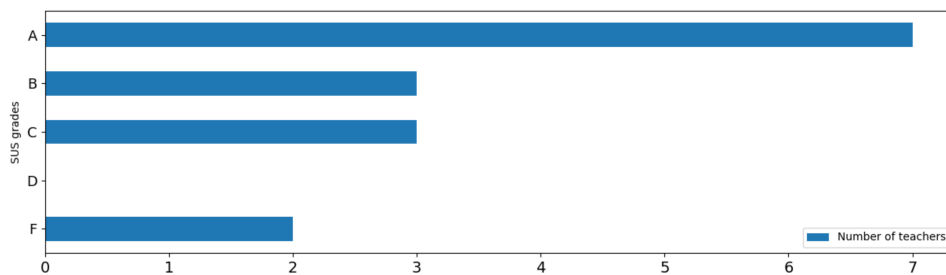


Figure 8.10 – Grades related to respondents' SUS scores

The next part aimed to investigate the usability of *iTeachApp* via the SUS questionnaire and some interface-related questions. To interpret the SUS scores, we exploited its grade, adjective and acceptability categories as illustrated in the figure 8.9³. These groups were used to interpret the results obtained from our respondents because it is the most commonly used method when using the SUS questionnaire (Alhadreti 2021). Thus, figure 8.10 shows that 7 teachers ranked *iTeachApp* in grade A, meaning that they were very satisfied with its use and thought it was excellent. While 3 other teachers were also very satisfied with it and found it good (grade B), 3 others were marginally satisfied and ranked it in grade C. On the other hand, we identified two teachers whose use of the

3. <https://measuringu.com/interpret-sus-score/>

platform was not satisfying and classified it as poor (grade F). The best scores were obtained by teachers in computer science given their experience with IT tools. In contrast, the two poor scores were obtained by a teacher in biochemistry-biology and another in information and communication sciences. Regarding the text used, 6 respondents found certain terms unclear, including homogeneity score, curiosity score and reflection axis, one of them stated : “I didn’t understand well how these indicators are calculated. I need more explanation and examples than the definition given in the interface”. The rest of the respondents consider them understandable and even one teacher said, “After reading the explanations, the choice of indicator labels seems relevant to me - no better to suggest !”. Regarding the radar visualization used to compare the two usage scores, 13 respondents found it relevant. However, the other two suggested the use of a bar chart.

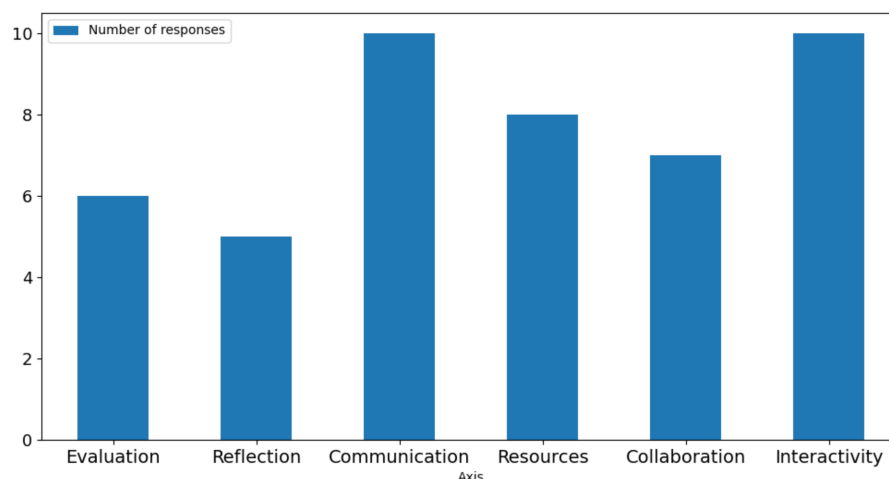


Figure 8.11 – Respondents’ preferred axes

The last part aimed to study the use of iTeachApp by teachers. A preference for using the app to view TA indicators over consulting recommendations was shown by teachers with 15 and 6 responses respectively. All respondents were interested in viewing their indicators, which means that the choice to design these TA indicators was appropriate. The recommendations may need to be improved to better fit teachers’ needs. Additionally, respondents had some preferences regarding the axes of our behavioral model, as shown in figure 8.11. Communication as well as interactivity and gamification were the most preferred axes. In contrast, the reflection axis was the least favorite axis, which may be due to its lack of understanding by many teachers. These results prove that those of the

quantitative study were obtained because of the display order of the axes and not really their preferences. Some teachers responded to the question regarding the reason behind choosing these axes, indicating that they use them the most in their courses. While one teacher said “they allow for more dynamic courses for students (not just consultation)”, a second said “they all look interesting! Some axes will be less relevant to me in my courses I think”. Thus, we deduce that the relevance of the axes is linked to courses of each teacher. For the TA indicators, most respondents preferred the LMS usage trends indicator as it was the clearest for them, followed by the curiosity score and finally the homogeneity score with 11, 5 and 3 responses respectively. In terms of possible improvements, teachers were interested in having (i) more information on the proposed functionalities, (ii) a direct synchronization of their traces to take into account recent courses and (iii) more clarity on their scores.

8.3 Synthesis

This chapter presents the experimentation we conducted at our university. Its purpose was to evaluate iTeachApp and, more generally, our approach that aims at engaging teachers in a learning process of their LMS. After its launch among teachers, two studies were conducted: (i) a quantitative study based on teachers’ traces on our application, in order to analyze how they really adopted it, and (ii) a second qualitative study through a questionnaire sent to participants in order to collect their opinions, expectations and at the same time validate the results of the first study. This experimentation had several limitations. First of all, the number of participants was not high because we launched it at the beginning of the school year which is a very busy period for teachers (bad timing). In addition, we did not have a wide diversity in teacher specialties, which may have biased our results, especially since most of them were computer scientists.

In general, the results showed that participants were interested in iTeachApp. Most of them found the model’s axes, indicators, and recommendations relevant. The app was easy to use and they had no problems accessing its various features. We also noticed some preferences in their use. For example, the “communication” and “interactivity and gamification” axes as well as the LMS usage trends were the most interesting for them. However, this experimentation revealed some problems with iTeachApp. Despite the method we applied to involve users and choose the right terms to use in iTeachApp, we realized the need to improve our panel of experts and imply more teachers in our approach. For example,

many teachers found the reflection axis and homogeneity score unclear. In addition, the lack of recent courses confused teachers because we did not include current year courses due to administrative issues. Finally, our feature recommendations lacked details on how to use them. This opens several perspectives for improving our work, including investigating the explainability of our analytics in order to provide teachers with more insights to understand our proposals. Furthermore, we need to work on adding more information with examples of how to implement the features we propose in the course environment. Since teachers are interested in axes based on courses, it is important to provide them with a view of the analysis by course for a more in-depth evaluation. Finally, we have to improve the process of extracting traces at our university level in order to allow the calculation of scores and recommendations at a higher rate. In the long term, we need to conduct another study to see the effect that iTeachApp can have on teachers' techno-pedagogical skills. Our features considered in the peer RS need also to be studied to determine their relevance. This can provide a very effective evaluation of our model, indicators and RSs.

CONCLUSION

In this last part, we first draw up an overview of what has been accomplished through this thesis and the different solutions it has brought about. Then, we propose different perspectives that this work has.

Synthesis of work and contributions of the thesis

The work presented in this thesis is situated within the framework of TEL in general and teaching analytics (TA) in particular. The problem of supporting and assisting teachers in the use of LMSs has been addressed by this research project. We started from the assessment that LMSs have become very complex and that teachers face several issues with their adoption. On the technical side, they lack support and on the organizational side, time for training is insufficient.

With the purpose of providing practical and theoretical solutions to this problem, we relied on literature reviews conducted in the first three chapters of this manuscript. We have situated our work in relation to the existing literature in order to better understand LMSs, to highlight the educational potential that TA can bring and identify the various needs of teachers. We have identified a lack of models for teacher self-evaluation in LMSs based only on their own traces without including those of students. We also recognized the importance of supporting teachers' self-reflection, self-awareness and self-evaluation in improving their practices. The state of the art served as a starting point to meet the objectives of this work: (i) **providing teachers with personal and social awareness tools to engage them in an LMS learning process**; (ii) **assisting them in these situations to improve their LMS use**.

We then examined, in the fourth chapter, the different existing methods to better exploit TA and provide teachers with a tool that best meets their needs. For this purpose, we have proposed the *TOM⁺⁺* methodology which extends the existing TOM proposed cycle by (Ndukwe 2021) with two layers of validation that allow for a more reliable results through the validation of PEs and teachers.

Our first research question **-how can teachers be supported to self-reflect, be**

self-aware, and self-evaluate their LMS use?- originates from literature. Indeed, researchers in psychology have proven that understanding and reflecting oneself is the initial step for change and improvement of a practice (Hew et al. 2007; Kraut 2001; Morin 2011). However, these concepts have not been studied in the context of teaching analytics to help teachers to improve their techno-pedagogical skills. Therefore, we have proposed a behavioral model of six axes to describe teachers' activities on the University's LMS with three teaching analytics indicators that support teachers' self-evaluation. The objective of this model is to offer teachers a self-evaluation tool along several dimensions, and thus allowing them to reflect on their LMS use and detect their strengths and weaknesses. TA indicators allow teachers to position themselves in relation to their colleagues and to support their self-awareness.

The behavioral model was designed on the basis of a qualitative analysis from interviews we had with several PEs as well as a quantitative analysis (principal component analysis) we conducted on teachers' activities on the LMS of our University. It describes in a comprehensive way teachers' practices on the institutional LMS through six axes: **(i) evaluation** (tools used by the teacher to evaluate their students), **(ii) reflection** (tools allowing teachers to collect students' feedback), **(iii) communication** (means of communication used by the teacher), **(iv) resources** (diversity of resources that the teacher makes available to students), **(v) collaboration** (tools promoting collaboration between students) as well as **(vi) interactivity and gamification** (interactive or playful activities used by teachers). Based on this model, we designed several TA indicators to provide teachers with self and social awareness. The first indicator is the LMS usage trend which is based on a clustering analysis (DBSCAN). It allows teachers to identify axes where they are considered as active and those where they are not, relatively to others teachers. This indicator relies on the social comparison theory which emphasizes the fact that comparison with others motivates people to improve and measure their personal development (Festinger 1954; Suls et al. 2002). In contrast, this comparison has some drawbacks (promote judgmental, biased and competitive attitudes (Dijkstra et al. 2008)), which led us to propose other teacher-related indicators to complement it. Thus, we have designed two different metrics for self-awareness based on our model: a curiosity and a homogeneity score. The former assesses the level of exploration of the platform by teachers (i.e. the variety of features they have used). This score was chosen because some works in literature have shown that curious individuals are more likely to learn and get more in-depth knowledge (Kesner Baruch et al. 2016; Litman 2008; Nurhayati et al. 2021). The second

score measures the regularity of teachers' use of the various features among their courses. This completes the curiosity score and gives the teacher a global view of their LMS use.

To answer our second question **-how can we assist teachers to enrich their use of the institutional LMS?-**, we exploited the fact that several works have studied the importance of the subjective norm (a social factor) in changing teachers' intention to use the LMS and enhance the teaching quality (Ajzen 1991; Coskuncay et al. 2013; Cigdem et al. 2015; Baran et al. 2014; Kopcha 2010). Therefore, we have proposed 3 recommender systems aiming at helping teachers to improve their practices in the university LMS. We provided them with a knowledge-based RS to recommend unused features by teachers per axis in order to motivate them to discover these functionalities and to help them to improve their courses' design. A second simple RS is offered to contact PEs if needed directly via our application. Finally, a hybrid recommender system (content-based and knowledge-based filtering) provides teachers with peer recommendations. It selects colleagues that expose better metric values, are not already over-recommended with respect to their own settings, and who are more physically and thematically close (i.e. physically close and similar teaching domains). This recommender system encourages teachers to interact with each other, assuming that the more they share common attributes, the more likely the recommendation will lead to a beneficial exchange.

Regarding our last question **-What is the most effective method to provide teachers and pedagogical engineers with a support tool while increasing its appropriation?-**, we attempted to instrument our contributions (model, indicators and recommendations) with a digital tool that best meets their expectations. We therefore followed a user-centered method to identify how best we could provide teachers and PEs with suitable TA to help them to improve their LMS skills and support teachers' needs respectively. User-centered methods allow to evaluate both the efficiency and the relevance of a tool and to anticipate some modifications (Khaled 2021). For this purpose, we addressed a questionnaire to teachers and conducted three interviews with PEs.

Regarding teachers' expectations, we noticed a great interest on their part to have a support tool that provides recommendations from close colleagues and pedagogical engineers. The majority of them were also open to help others in order to improve their practices on the LMS. With respect to these results as well as those of the interviews conducted with PEs, we were able to select relevant types of visualizations and recommendations for teachers within an application we named iTeachApp. It was also designed to build a digital trust and offer analytics with a proper degree of explainability.

After launching our application, we conducted an experimentation at our University. Its objective was to evaluate the utility, usability and use of iTeachApp by teachers. Access was given to teachers who had previously agreed on testing it. Then, we conducted a quantitative study based on teachers' traces to analyze how they really adopted it. In a second step, we conducted a qualitative study through a questionnaire sent to teachers with the objective to collect their feedback and suggestions. Collected answers revealed considerable interest in our behavioral model, TA indicators, and recommender systems. Some axes were preferred by teachers who specified that their choice is grounded in the nature of their courses. Regarding our indicators, the LMS usage trends were the most interesting to them since it permitted to see their overall use of the different axis features.

Limitations and perspectives

Limitations

The research we have conducted throughout this thesis has several limitations.

Our behavior model is based on results of both qualitative and quantitative analyses we carried out. While this model allows to describe in an intelligible way teachers' activities on the LMS and appears consistent with both current usage we can observe through traces and human expert knowledge, these analyses still have several limitations. We have integrated teachers' main traces on the University's LMS to analyze their behavior, and then only computed features related to teachers' manipulation of different LMS functionalities. However, mining features at a finer level, such temporal features, could yield more insightful results regarding teachers' behavior. On the other hand, many teachers use other technologies to manage their teaching we do not have access to. Moreover, our study does not take into account what happens in the class, outside the technological environment, thus two different courses may be represented in the same way by our model. Teachers' practices are not limited to those related to LMSs. It is therefore important to consider all teachers' activities, whether in the face-to-face environment or when using various TELs.

Internally, the model is representative of the teachers' behavior, which is bound to evolve as well as the population itself (new teachers, others leaving the institution). Clusters must therefore be recalculated but the optimal interval is not known. The structure of the model (axes) also depends on functionalities proposed by the LMS and partly on

their use by teachers. Hence, this structure itself is not stable over time. A monitoring of the model becomes a requirement by adding or removing certain axes' functionalities, creating new ones or recomposing them. These changes may render analyses of teachers' evolution delicate in the long run. Therefore, automating axes' creation is an interesting avenue to explore in order to adapt more easily to the structure's evolution.

Our curiosity and homogeneity indicators have been defined to be simple and explainable. However, teachers have different levels of curiosity that we cannot detect with the current formula, and their homogeneity with respect to their courses is not refined. This can be improved by considering more features that represent the depth of detail teachers can achieve when using different LMS functionalities.

Regarding our recommender systems, we have identified a limitation related to the unused features RS. As a matter of fact, it may suggest features that the teacher already knows but does not want to use, possibly because they are not adapted to their course or/and their teaching style, etc.

Furthermore, our study considers all teachers the same way. Although this has the advantage of identifying context-independent trends, taking the context into account could provide more refined profiles, particularly with the inclusion of the teaching field and the targeted diploma or academic year. However, the scarcity of our dataset did not allow us to apply such differential study.

On the other hand, part of our dataset concerns the time of the lockdown caused by COVID, where all courses were performed remotely with other tools (Teams, Zoom ..). While the lockdown itself remains a short period, teachers may have changed their habits afterwards, and our model may not be valid anymore if such changes occurred and will remain durably. A dedicated study on this problematic is required.

In terms of experimentation, we did not have a large number of participants and most of them were computer scientists. Hence, there is a risk of having a non-representative sample. To address this issue, further experiments have to be conducted with teachers in a more convenient time periods. In addition, the experiment revealed a limited understanding of our analytics by teachers. Many were not able to understand the meaning of TA indicators or axes, even though all terms were discussed with PEs before launching the application. This indicates that the way we involved teachers and pedagogical engineers needs to be reviewed and improved in order to anticipate such problems.

Perspectives

The reflections carried out during this work of thesis open numerous prospects:

Analytics. The first perspective is part of improving the existing solution (model, indicators and recommendations). It concerns the refinement of our model with the inclusion and analysis of new features that would consolidate our axes, such as time related features to express regularity or skill oversight, etc. Other features may also provide new axes, as those related to teachers' activities in face-to-face classrooms, or to the use of external tools, etc.

The usage scores (curiosity and homogeneity scores) can also be improved by adding a granularity level which takes into account further specifics of what teachers do in the LMS. It can be calculated by considering the amount of time teachers spend using each feature, how often they use it, and how many settings they manipulate. For example, if a teacher has already tested a quiz activity, we can investigate the character of this interaction: time spent during testing the activity, number of manipulations (creating, editing, or deleting), and number of settings tested (e.g. using the timing, grade, and feedback options). This contribute to successfully distinguish between teachers who just tested the feature and left (didn't need it or couldn't use it) and those who were more curious and wanted to master it better. Moreover, this granularity level can improve the homogeneity score as well. It can provide a more refined study of teachers' consistency of LMS use relative to their courses. For example, the level of granularity can be calculated for each course, and followed by the computation of their standard deviation. A higher value of the latter (with a homogeneity score of 100%) indicates that the teacher uses all features of the axis in all their courses but not in the same way. In other words, the time spent using them, the frequency of use and the number of settings used are not the same in all of their courses.

Regarding recommendations, we intend to improve the unused features RS by including more information with some examples of their integration in the course' design. A hybrid RS can be also adopted to combine the current knowledge filtering with a collaborative one. Teachers could then rate the relevance of of each recommended feature. By leveraging similarities between teachers (specialties, courses, departments, etc.), features can be suggested based on a similar teacher interest. This can minimize the risk of suggesting functionalities that teachers do not want to use on their own.

Model structure and teacher support. Once more data is available on Umtice, we will be able to provide teachers with course-based analytics. They then could compare

their LMS use by course, for a more refined self-evaluation. It also serves our goal to propose more context-specific recommendations for each course.

To consider the overall practice of a teacher, it may be interesting to integrate a customizable dimension that aims to take into account tools used outside the LMS and on what happens in classrooms. This can be done by defining surveys and calculating indicators related to teachers' practices in general such as: how many external tools do you use? do you offer collaborative activities to your students? etc. Through this process, teachers can position their use of the LMS within their overall practice. For example, they could compare their use of collaborative activities in the classroom with those used within the LMS or with other tools. Thereby, awareness on practice diversity could be extended and give valuable insight to improve their courses.

To better support teachers, we aim at exploring mentoring models of technology integration such as proposed by (Kopcha 2010). Their model depicts how a mentor can intervene in the interaction of multiple barriers (time, beliefs, access, professional development, culture) upon teachers learning to use technology and offers a number of strategies toward technology integration, such as establishing a culture of technology integration, modeling technology use, and creating teacher leaders. The objective here is to leverage these different strategies to improve our contributions and provide more strategies to support teachers in the LMS use.

Method and application. The method we used involves experts who are, in our case, pedagogical engineers. However, designing the application only with them showed some limitations (the choice of terms was not relevant for teachers). Thus, our method needs to be improved by getting teachers more involved in the design process. We need to find the best way to apply teaching analytics in order to help teachers. The user-centered approach must be put forward through interviews, retrospective analysis of users to get their needs, problems and how they are interpreting our proposals. It could be also interesting to organize workshops with them. This might help to better explain the project to teachers, help them in testing the application and choosing the appropriate terms to use in it. Furthermore, understandable terms may be different from one teacher to another. Thus, we also need to identify good practices for choosing the most appropriate vocabulary for teachers by collaborating with a panel of experts who should also be chosen based on well-defined guidelines. From an analytical perspective, enhancing teachers' understanding of terms we use can be achieved by exploring the explainability of our model, indicators, and recommendations. This includes explaining why the model gave such results by providing

information in a complete semantic format that is accessible to users (Robbins 2019). In essence, experts in computer and education sciences need to collaborate with the objective of improving teachers' understanding of their analytics.

Regarding our application, it is important to improve the trace extraction process at our University to allow the calculation of real-time scores and recommendations. Therefore, an administration module can be added to manage this extraction as well as the automatic calculation of the behavioral model's axes. While there will always be an interpretation part that we can't automate, axes' analysis can be simplified by creating a dedicated interface in iTeachApp. Researchers can log in to add features, run the clustering analysis and create the axes after validation with experts. In the long term, we aim to transform iTeachApp into a Moodle plugin to simplify its use and facilitate its re-use for any other university LMS.

Experimentations. Regarding iTeachApp experimentation, we intend to carry it out in other universities in France. As a matter of fact, we have already been contacted by many universities on the matter such as Lille and Rouans. For the University of Lille, we have already started to organize meetings in order to (i) adapt the application to their LMS and technological environments, (ii) discuss the changes that Lille's pedagogical engineers would like to bring to iTeachApp, and (iii) plan an experimentation with teachers. Conducting such an experiment requires a lot of preparation, particularly in terms of technical aspects for the implementation management. On the other hand, our proposal can be reinforced by collecting feedback from a larger number of teachers and pedagogical engineers, thus contributing to the further improvement of our solution.

We also plan to study the impact that our application could have on teachers' practices. In other words, over the long term, we want to determine whether teachers will really engage in a process of learning to enhance their pedagogical practices or not in the LMS. This can be done by studying the teachers' course environments before and after using iTeachApp. Moreover, the peer recommendation system should be validated and enriched through a dedicated experiment to see how it is adopted by teachers (if they really help each other and if it helps them improve their practices, etc.).

Pedagogical design. Mastering an LMS is not limited to only mastering its functionalities, a correct pedagogical fit is also required. Teachers need to accurately design their pedagogical scenarios in order to adapt them to the digital tool. This opens another perspective, that of studying the relevance of pedagogical scenarios when using an LMS. By doing so, researchers can (i) define criteria related to the relevance of a pedagogical

scenario and (ii) propose a computer-based formalism of teaching practices. In a second step, this formalism should allow to automatically detect teaching practices, and thus providing teachers with personalized visualization and recommendation tools aiming to facilitate pedagogical scenarios building.

Finally, (Sergis et al. 2017) has proposed the concept of Teaching and Learning Analytics (TLA) as a complementary synergy between Teaching Analytics and Learning Analytics to support teachers' inquiry process. However, this concept can also be leveraged to support teachers in their pedagogical design. Researchers can analyze teachers' pedagogical scenario in the LMS and study its correlation with students' actions and possibly their grades as well. This can help identify how teachers' actions and designs can affect students' behavior in the LMS and their overall learning.

We conclude this thesis with the observation that the research questions have not only been answered, but the challenging and promising field of teaching analytics will transform teaching in the upcoming decade. The potential is great, the challenges are, too. The research conducted for this work condensed into a novel type of tool is an important milestone in this pioneering effort to make teaching analytics accessible and understandable. Furthermore, this work can initiate numerous reflections related to the mastery of technology in the service of pedagogy.



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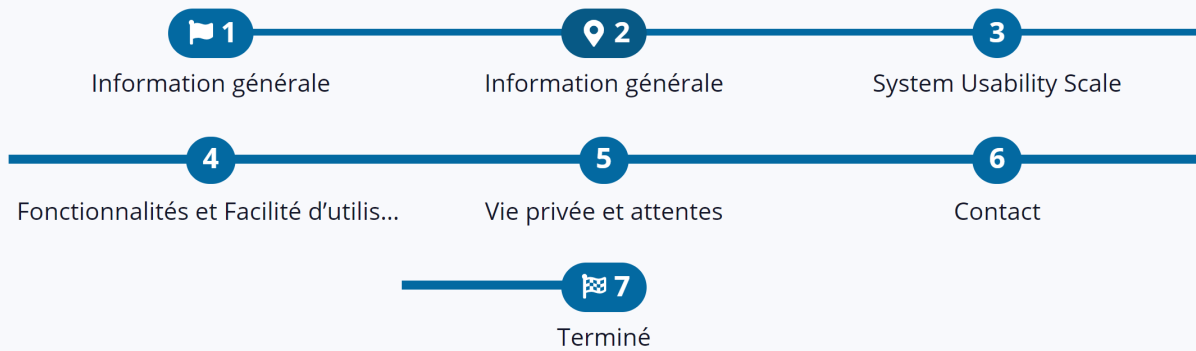
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APPENDIXES

A Umtice usability questionnaire

A.1 Original version



Site *

- Sélectionner -



UFR *

Spécialité *

Sexe *

- Sélectionner -



Age *

- Sélectionner -

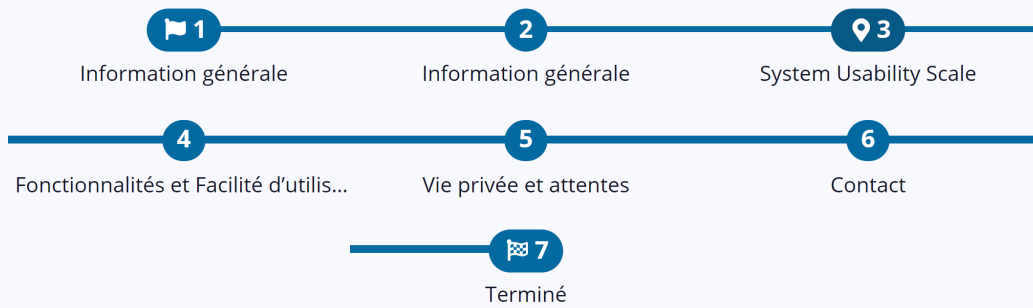


Nombre d'années d'expérience *

Nombre de cours enseignés *

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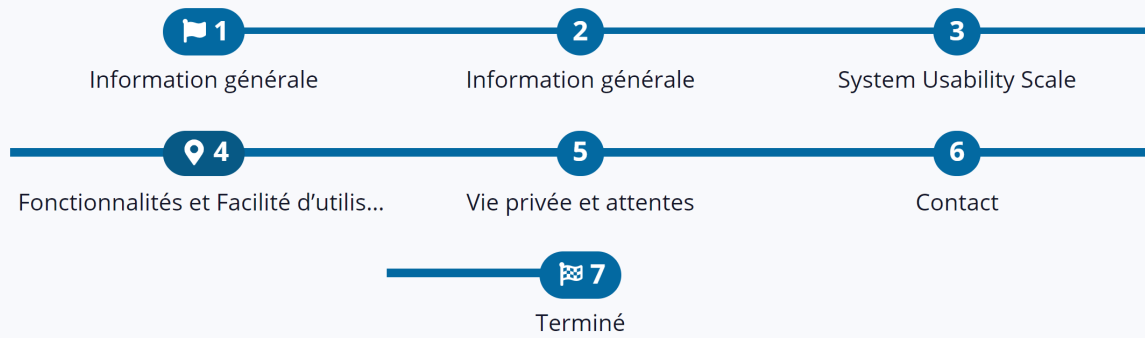


System Usability Scale *

	Pas du tout d'accord	Plutôt pas d'accord	Neutre	Plutôt d'accord	Tout à fait d'accord
Je pense utiliser Umtice fréquemment *	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Je pense qu'Umtice est inutilement complexe *	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Je pense qu'Umtice est facile d'utilisation *	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Pour utiliser Umtice, je fais appel au support technique proposé *	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Je trouve que les fonctionnalités d'Umtice sont bien intégrées *	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Je trouve qu'il y a beaucoup trop d'incohérences dans cette plateforme *	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Je pense que la plupart des gens apprennent très rapidement à utiliser Umtice *	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Je trouve Umtice vraiment très lourd à utiliser *	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Je me suis senti très confiant en utilisant Umtice *	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
J'ai dû apprendre beaucoup de choses avant de pouvoir utiliser Umtice *	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

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PAGE SUIVANTE >



Fonctionnalités *

	Pas du tout d'accord	Plutôt pas d'accord	Neutre	Plutôt d'accord	Tout à fait d'accord
Sur Umtice, j'utilise fréquemment des activités de communication (forum, chat) *	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Sur Umtice, j'utilise fréquemment des activités de collaboration (blogs, wiki, atelier..) *	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Sur Umtice, j'utilise fréquemment des activités d'évaluation (quizz, devoir...) *	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Sur Umtice, j'utilise fréquemment la plateforme pour déposer des ressources de cours (fichier, livres, url ..) *	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Sur Umtice, j'utilise fréquemment des activités ludiques et attractives (jeux, gallery, images ..) *	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Sur Umtice, j'utilise fréquemment des fonctionnalités pour avoir un retour de mes étudiants sur mon cours (sondages, consultation) *	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

Sur Umtice, j'utilise fréquemment d'autre type de fonctionnalité :

Facilité d'utilisation *

	Pas du tout d'accord	Plutôt pas d'accord	Neutre	Plutôt d'accord	Tout à fait d'accord
J'aimerais découvrir de nouvelles fonctionnalités sur Umtice dans le but d'améliorer mes enseignements *	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Mes collègues m'encouragent à utiliser Umtice *	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Je rencontre de nombreuses difficultés dans l'utilisation de la plateforme pour préparer ou réaliser mes cours *	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Je ne maîtrise pas Umtice car je n'ai pas le temps d'apprendre *	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Je ne maîtrise pas Umtice car je ne trouve pas d'aide *	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

Je ne maîtrise pas Umtice pour une autre raison :

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Vie privée *

Pas du tout d'accord Plutôt pas d'accord Neutre Plutôt d'accord Tout à fait d'accord

Je suis favorable à la collecte de mes traces sur le LMS pour m'aider dans son utilisation *

Si je rencontre un problème sur Umtice, je demande de l'aide à : *

- un collègue proche
- un enseignant de l'université
- un ingénieur pédagogique
- je ne souhaite pas demander d'aide
- autre

Si je rencontre un problème sur Umtice, je demande de l'aide à d'autres personnes que citées précédemment :

Si un collègue me demande de l'aide sur une fonctionnalité d'umtice que je maîtrise :

- Je l'aide volontiers
- Je l'aide selon ma disponibilité
- Je n'ai pas pour habitude de répondre à ce type de sollicitation
- Autre

Je suis intéressé(e) par un outil complémentaire à Umtice pour : *

- m'auto-évaluer
- obtenir de l'aide de mes collègues
- avoir des retours (feedbacks) sur mon utilisation d'Umtice
- obtenir des recommandations des pairs
- Autre

Si autre, voici par quoi je serais intéressé(e) :

Fonctionnalités manquantes *

Pas du
tout
d'accord

Plutôt pas
d'accord

Neutre

Plutôt
d'accord

Tout à fait
d'accord

Je pense qu'il manque des fonctionnalités importante à Umtice pour être utilisé par la plupart des enseignants de l'Université *



Quelles pourraient-être ces fonctionnalités où les améliorations à apporter pour pallier ce manque ?

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Si vous êtes intéressé(e) par échanger plus longuement sur le sujet d'Umtice dans le cadre des recherches académiques menées sur les Teaching Analytics, n'hésitez pas à nous communiquer votre adresse de courriel :

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SOUMETTRE

A.2 English version

A. General information

1. Site*
 - Laval
 - Le Mans
2. Service *: [Text]
3. Specialty *: [Text]
4. Gender*
 - Male
 - Female
 - Other
5. Age *
 - Between 20 and 35 years' old
 - Between 35 and 50 years' old
 - 50 years old and more
6. Years of experience*: [Number]
7. Number of courses taught*: [Number]

B. Umtice usability

1. System Usability Scale [Likert scale]
 - I think that I would like to use this system frequently. *
 - I found the system unnecessarily complex. *
 - I thought the system was easy to use. *
 - I think that I would need the support of a technical person to be able to use this system. *
 - I found the various functions in this system were well integrated. *
 - I thought there was too much inconsistency in this system. *
 - I would imagine that most people would learn to use this system very quickly. *
 - I found the system very cumbersome to use. *

- I felt very confident using the system. *
 - I needed to learn a lot of things before I could get going with this system. *
2. Functionalities [Likert scale]
- On Umtice, I frequently use communication activities (forum, chat) *
 - On Umtice, I frequently use collaborative activities (blogs, wiki, workshop...) *
 - On Umtice, I frequently use evaluation activities (quizzes, assignments...) *
 - On Umtice, I frequently use the platform to upload course resources (files, books, url ...) *
 - On Umtice, I frequently use playful and attractive activities (games, gallery, images ...) *
 - On Umtice, I frequently use features to get feedback from my students on my courses (surveys, consultation) *
 - On Umtice, I frequently use other kind of features: [Text]
3. Ease of use [Likert scale]
- I would like to discover new features on Umtice in order to improve my teaching *
 - My colleagues encourage me to use Umtice *
 - I encounter many difficulties in using the platform in order to plan or carry out my courses *
 - I don't master Umtice because I don't have time to learn *
 - I don't master Umtice because I can't find help *
 - I don't master Umtice for another reason: [Text]

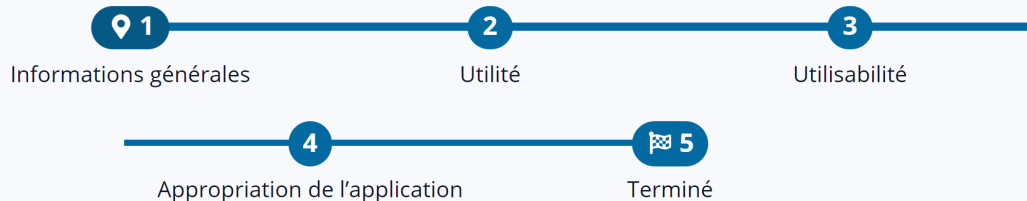
C. Privacy and expectations

1. I agree to collect my traces on the LMS to help me in its use* [Likert scale]
2. If I encounter a problem on Umtice, I ask for help from*: [multiple choice]
 - a close colleague,
 - a teacher from the university,
 - an pedagogical engineer,
 - I do not wish to ask for help
 - other

3. If I have a problem on Umtice I will ask for help from other people than the ones mentioned above: [Text]
4. If a colleague asks me for help on an Umtice functionalities that I master*:
 - I help him gladly,
 - I help him according to my availability,
 - I do not usually respond to this type of request.
5. I am interested in a complementary tool to Umtice for*: [multiple choice]
 - evaluate myself,
 - get help from my colleagues,
 - get feedbacks on my use of Umtice,
 - get recommendations from peers,
 - other
6. If other, here is what I would be interested in: [Text]
7. I think Umtice is missing some important features to be used by most teachers at the University * [Likert scale]
8. What could be these features or improvements to fill this gap? [Text]
9. If you are interested in a more in-depth exchange on the topic of Umtice in the context of an academic research on teaching analysis, please feel free to send us your email address [Email]

B iTeachApp evaluation questionnaire

B.1 Original version



Site *

- Le Mans
- Laval

UFR *

Sexe *

- Homme
- Femme
- Autre

Age *

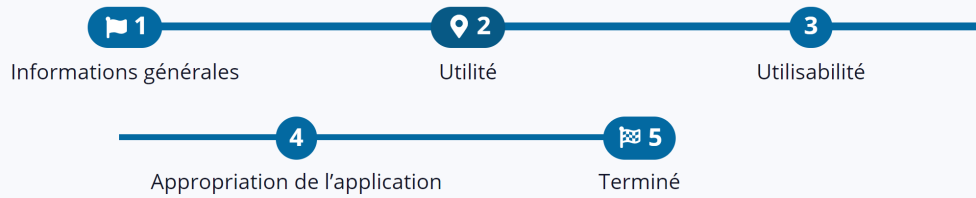
- Entre 20 et 35 ans
- Entre 35 et 50 ans
- 50 ans et plus

Nombre d'années d'expérience dans l'utilisation des outils numériques *

Nombre de cours actuellement enseignés en utilisant Umtice *

Nombre de cours actuellement enseignés indépendamment d'Umtice *

Si vous souhaitez discuter plus longuement du sujet de l'application iTeachApp dans le contexte des recherches académiques, n'hésitez pas à nous communiquer votre adresse électronique



Je trouve que la représentation de mon activité sur Umtice par axe est pertinente pour me situer dans ma maîtrise de l'outil *

- Oui
 Non

Si non, pourquoi ?

Les six axes proposés représentent correctement mon utilisation sur Umtice *

- Oui
 Non

y-a-t'il des manques ou des axes que vous estimez incorrects ou inappropriés ?

Les différents indicateurs par axe (tendance d'utilisation, score de curiosité et score d'homogénéité) me sont utiles pour faire évoluer mon utilisation d'Umtice *

- Oui
 Non

Si non, quelles informations pourraient m'être utiles ?

Je trouve que les recommandations en général me motivent à enrichir mes pratiques sur Umtice *

- Oui
- Non

Si non, quels autres types de recommandations pourraient m'être pertinentes ?

En ce qui concerne les activités d'Umtice qui me sont recommandées par axe *

- J'ai déjà commencé à les découvrir.
- Je prévois de les tester ultérieurement.
- Cela ne m'intéresse pas.

Aucun des choix précédents ne vous correspond, les activités vous intéressent néanmoins, que pourrions nous proposer pour vous accompagner?

En ce qui concerne les collègues proches proposés par axe *

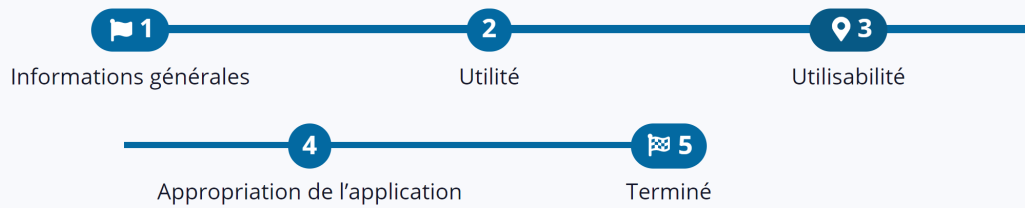
- J'ai déjà contacté un ou plusieurs collègues.
- Je prévois de les contacter prochainement.
- Je prévois de les contacter en cas besoin.
- Je ne ressens pas le besoin de contacter mes collègues.

Si vous avez déjà contacté des collègues, avez-vous reçu une réponse ?

- Oui, et nous avons déjà échangé sur le sujet.
- Oui, et nous prévoyons d'échanger sur le sujet.
- Oui, mais le collègue n'a pas pu répondre favorablement à ma demande.
- Non

En ce qui concerne les recommandations des ingénieurs pédagogiques par axe *

- Je les ai déjà contactés.
- Je prévois de les contacter prochainement.
- Je prévois de les contacter en cas de besoin.
- Je ne ressens pas le besoin de les contacter.



System usability scale *

	Pas du tout d'accord	Plutôt pas d'accord	Neutre	Plutôt d'accord	Tout à fait d'accord
Je voudrais utiliser ce système fréquemment *	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Ce système est inutilement complexe *	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Ce système est facile à utiliser *	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
J'aurais besoin du soutien d'un technicien pour être capable d'utiliser ce système *	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Les différentes fonctionnalités de ce système sont bien intégrées *	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Il y a trop d'incohérences dans ce système *	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
La plupart des gens apprendront à utiliser ce système très rapidement *	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Ce système est très lourd à utiliser *	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Je me suis senti·e très en confiance en utilisant ce système *	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
J'ai eu besoin d'apprendre beaucoup de choses avant de pouvoir utiliser ce système *	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

Globalement, j'accède facilement aux informations que m'offre l'application *

Oui

Non

Si non, que proposeriez-vous comme modification ?

Je trouve que les noms et la description des axes et des indicateurs sont suffisamment compréhensibles *

Oui

Non

Si non, quels termes vous posent problème ?

Je pense que le choix de la visualisation en radar pour résumer les deux scores (curiosité et homogénéité) est pertinent *

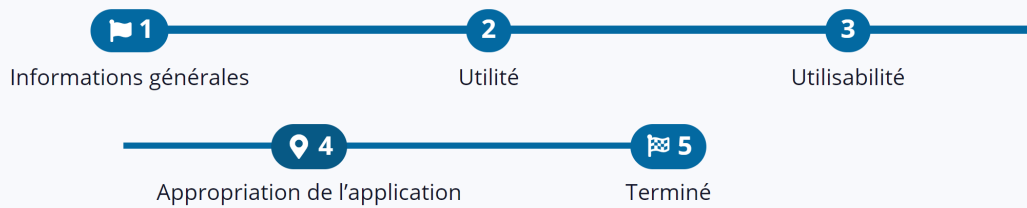
Oui

Non

Si non, quelle représentation graphique vous semblerait plus pertinente ?

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Je préfère utiliser l'application pour *

- consulter mes indicateurs.
- consulter mes recommandations.

J'ai une préférence dans les axes proposés *

- évaluation
- réflexion
- communication
- ressources
- collaboration
- interactivité et gamification

En quoi ces axes m'intéressent plus que d'autres ?

Je suis intéressé-e particulièrement par les indicateurs suivants *

- Tendance d'utilisation
- Score de curiosité
- Score d'homogénéité

Pourquoi?

J'ai rencontré des problèmes techniques lors de l'utilisation de l'application iTeachApp *

Oui

Non

Si oui, quels sont-ils ?

Selon vous, quelles pourraient être les fonctionnalités ou les améliorations à apporter à iTeachApp ?

Commentaires libres

[< PAGE PRÉCÉDENTE](#)

[SOUMETTRE](#)

B.2 English version

A. General information

1. Site*
 - Laval
 - Le Mans
2. Service *: [Text]
3. Specialty *: [Text]
4. Gender*
 - Male
 - Female
 - Other
5. Age *
 - Between 20 and 35 years' old
 - Between 35 and 50 years' old
 - 50 years old and more
6. Number of years of experience in the use of digital tools*: [Number]
7. Number of courses currently taught using Umtice*: [Number]
8. Number of courses currently taught independently of Umtice*: [Number]
9. If you would like to further discuss the topic of the iTeachApp in the context of academic research, please feel free to send us your email address: [Email]

B. Utility

1. I find the representation of my activity on Umtice by axis is relevant to situate me in my mastery of the tool*:
 - Yes
 - No
2. If not, why? [TEXT]
3. The six proposed axes represent correctly my use of Umtice*:

- Yes
 - No
4. If not, what do you think is missing? [TEXT]
5. The different indicators per axis (usage trend, curiosity score and homogeneity score) are useful for me to evolve my use of Umtice*:
- Yes
 - No
6. If not, what information could be useful to me? [TEXT]
7. I find that the recommendations in general motivate me to enrich my practices on Umtice*:
- Yes
 - No
8. If not, what other types of recommendations might be relevant to me? [TEXT]
9. Regarding Umtice activities that are recommended to me by axis*:
- I have already started to discover them
 - I plan to try them later
 - I am not interested
10. None of the previous choices correspond to you, but you are interested in the activities, what could we propose to accompany you? [TEXT]
11. Regarding the close colleagues proposed by axis*: [MULTIPLE CHOICE]
- I have already contacted one or several colleagues
 - I plan to contact them soon
 - I plan to contact them if necessary
 - I do not feel the need to contact my colleagues
12. If you have already contacted colleagues, have you received a response? *:
- Yes, and we have already talked about it
 - Yes, and we plan to discuss the issue
 - Yes, but the colleague could not respond favorably to my request
 - No

13. Regarding the recommendations of the pedagogical engineers by axis*:

- I have already contacted them
- I plan to contact them soon
- I plan to contact them if needed
- I do not feel the need to contact them

C. Usability

1. System usability scale questionnaire: [Likert Scale]

- I think that I would like to use this system frequently. *
- I found the system unnecessarily complex. *
- I thought the system was easy to use. *
- I think that I would need the support of a technical person to be able to use this system. *
- I found the various functions in this system were well integrated. *
- I thought there was too much inconsistency in this system. *
- I would imagine that most people would learn to use this system very quickly. *
- I found the system very cumbersome to use. *
- I felt very confident using the system. *
- I needed to learn a lot of things before I could get going with this system. *

2. Overall, I have easy access to the information the application offers*:

- Yes
- No

3. If not, what would you suggest to change? [TEXT]

4. I find the axis and indicators names understandable*:

- Yes
- No

5. If not, which terms are causing you problems? [TEXT]

6. I think the choice of radar visualization to summarize the two scores (curiosity and homogeneity) is relevant*:

- Yes
 - No
7. If not, which graphical representation would you find more relevant? [TEXT]

D. Appropriation of the application

1. I prefer to use the application to*: [MULTIPLE CHOICE]
- consult my indicators
 - consult my recommendations
2. I have a preference in the proposed axes*: [MULTIPLE CHOICE]
- evaluation
 - reflection
 - communication
 - resources
 - collaboration
 - interactivity and gamification
3. Why are these axes of interest to me more than others? [TEXT]
4. I am particularly interested in the following indicators*: [MULTIPLE CHOICE]
- Usage trend
 - Curiosity score
 - Homogeneity score
5. Why? [TEXT]
6. I have experienced technical problems while using the application iTeachApp *:
- Yes
 - No
7. If yes, what are they? [TEXT]
8. What features or improvements do you think could be made to iTeachApp? [TEXT]
9. Free comments: [TEXT]

C Tracing model

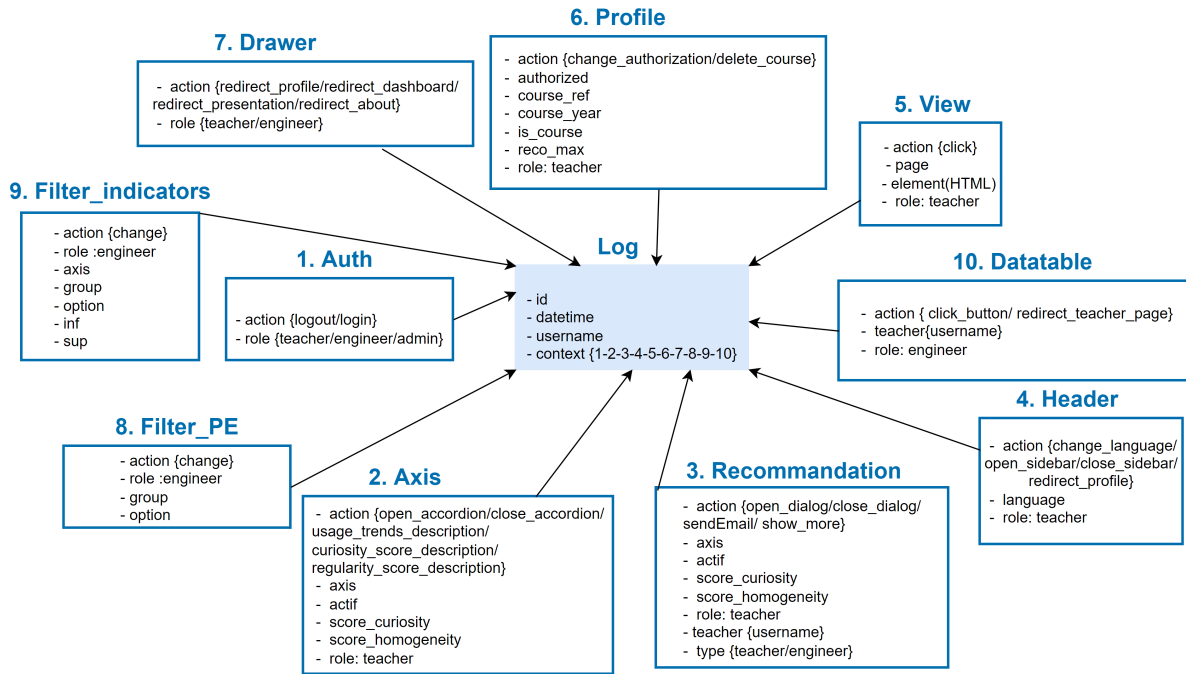


Figure L – Diagram of the log model.

Titre : Teaching analytics : support à l'évaluation et à l'assistance à la conception pédagogique par l'intelligence artificielle

Mot clés : teaching analytics, learning Management System, auto-évaluation, clustering, recommandation

Résumé : Cette thèse s'inscrit dans le cadre de l'utilisation des *Teaching Analytics* pour analyser les comportements des enseignants et les assister dans l'utilisation des systèmes de gestion de l'apprentissage (*Learning Management System* - (LMS)). Les *Teaching Analytics* (TA) se réfèrent aux méthodes et aux outils pour aider les enseignants à analyser et à améliorer leurs conceptions pédagogiques, et plus récemment, à l'analyse de la manière dont ceux-ci dispensent leurs enseignements. Notre objectif est d'exploiter ce domaine afin d'aider les enseignants à évaluer leurs comportements sur leur LMS institutionnel. In fine, nous souhaitons doter les enseignants d'outils leur permettant de s'engager eux-mêmes dans des situations d'apprentissage visant à améliorer leurs utilisations du LMS, et de soutenir ces situations par le biais de feedbacks et d'un support à l'apprentissage par les pairs.

Afin d'atteindre cet objectif, et puisque nous considérons l'enseignant dans une situation d'apprentissage potentielle, nous cherchons d'abord à concevoir un modèle d'enseignant, comme nous le ferions pour un apprenant. Nous avons investigué dans ces travaux trois questions de recherche : **(i)** Comment aider les enseignants à prendre conscience de leur propre situation et à s'auto-évaluer sur l'utilisation de leurs LMS ?, **(ii)** Comment aider les enseignants à enrichir leur utilisation du LMS institutionnel ? et enfin **(iii)** Comment fournir aux enseignants et aux ingénieurs pédagogiques un outil de soutien mieux adapté à leurs besoins ?

Pour répondre à nos questions de recherche, nous avons conçu un modèle d'éva-

luation sur la base (i) d'une analyse qualitative à partir d'entretiens que nous avons eus avec plusieurs ingénieurs pédagogiques et (ii) d'une analyse quantitative que nous avons réalisée sur trois années d'activités d'enseignants sur le LMS de l'Université.

L'objectif de l'étude qualitative était de collecter des données qui pourraient être utiles pour comprendre le comportement actuel des enseignants sur les LMS du point de vue des ingénieurs pédagogiques, car ils ont une expérience vis-à-vis des enseignants. Pour réaliser cette étude, nous avons choisi de mener des entretiens semi-structurés. D'autre part, une étude quantitative a été menée pour déduire des conclusions statistiquement mesurables sur le comportement des enseignants, complémentaire aux résultats de l'étude qualitative. Une analyse en composantes principales (ACP) nous a permis dans un premier temps de réduire la dimensionnalité de nos données afin de pouvoir identifier des groupes distincts de profil d'enseignants. Ces deux études ont été exploitées conjointement pour concevoir un modèle explicable qui catégorise l'utilisation de la plateforme par les enseignants et ainsi permettre à ces derniers d'évaluer leurs pratiques selon plusieurs aspects (i.e., axes du modèle). Par la suite, nous avons défini différents indicateurs de TA : La tendance d'utilisation du LMS et des scores d'utilisation. La dernière phase de notre méthodologie consiste à instrumentaliser les résultats obtenus dans un outil d'accompagnement principalement dédié aux enseignants qui comprend des tableaux de bord permettant de visualiser des informations sur le comportement des enseignants et des recomman-

datations.

Le modèle comportemental que nous avons conçu décrit les pratiques des enseignants sur les LMS à travers six axes majeurs : l'évaluation (outils utilisés par l'enseignant pour évaluer ses étudiants), la réflexion (outils permettant aux enseignants de collecter les feedback des étudiants), la communication (moyens de communication utilisés par l'enseignant), les ressources (diversité des ressources que l'enseignant met à la disposition des étudiants), la collaboration (outils favorisant la promotion de la collaboration entre les étudiants) ainsi que l'interactivité et la gamification (activités interactives ou ludiques utilisées par les enseignants). À partir de ce modèle, nous avons conçu un premier indicateur de TA, la tendance d'utilisation du LMS. Fondé sur une analyse en *clustering* afin d'identifier des groupes d'enseignants ayant une utilisation particulière selon chaque axe, celui-ci offre un moyen de fournir un support à l'*awareness* sociale (i.e., la comparaison aux pairs). Dans une perspective d'un support à l'*awareness* individuelle, deux autres indicateurs viennent fournir un moyen simple d'évaluer sa pratique. Toujours dans le contexte des axes du modèle, nous avons donc proposé des scores pour exprimer (i) la curiosité de l'enseignant (la variété de l'utilisation de la plateforme indépendamment du temps) et (ii) l'homogénéité d'utilisation des différentes facettes du LMS (la régularité de l'utilisation des différentes fonctionnalités relatives à un axe).

Nous avons par la suite proposé 3 systèmes de recommandation s'appuyant sur ce modèle et ces indicateurs visant à aider les enseignants à améliorer leurs pratiques dans le LMS de l'université. Un premier système de recommandation s'attache à proposer les fonctionnalités inexploitées par l'enseignant selon chaque axe afin de les motiver dans leur découverte et de les aider à améliorer la conception de leurs cours. Un second système de recommandation d'ingénieurs pédagogique simple a été mis en place pour faciliter la mise en place d'un dialogue entre l'enseignant et ces derniers. Enfin, un système de recommandation hybride (basé sur le contenu et les connaissances) a été élaboré pour per-

mettre aux enseignants de recevoir des recommandations de pairs. Celui-ci sélectionne les collègues qui présentent de meilleures valeurs métriques selon l'axe du modèle choisi, qui ne sont pas déjà sur-recommandés (i.e., qui n'ont pas déjà été recommandés plus de fois qu'ils ne le souhaitent), et qui sont les plus proches physiquement et thématiquement (c'est-à-dire, respectivement, dont les départements d'enseignement sont géographiquement proches ou identiques, et dont le domaine d'enseignement est proche). Ce dernier système encourage les enseignants à interagir entre eux, en partant du principe que plus ils partagent d'attributs communs, plus la recommandation aura des chances d'être effective.

Nous avons ensuite adopté une approche centrée utilisateur afin de valider le modèle comportemental que nous avons conçu préalablement et de pouvoir l'instrumenter de la façon la plus appropriée à l'enseignant. Pour ce faire, nous avons élaboré un questionnaire destiné aux enseignants, et nous avons également programmé trois entretiens avec les ingénieurs pédagogiques de l'université. Par conséquent, la première version fonctionnelle de notre application de soutien iTeachApp a été développée en tenant compte des préférences des enseignants et des remarques des ingénieurs pédagogiques.

iTeachApp est une application web dédiée aux enseignants et aux ingénieurs pédagogiques pour (i) fournir aux premiers des fonctionnalités d'auto-évaluation et de recommandations, et (ii) permettre aux seconds de détecter les enseignants ayant des besoins spécifiques et les enseignants ayant un profil d'expert.

Nous avons mené une première expérimentation de cette plateforme à l'échelle de l'université. Son objectif était d'évaluer l'utilité, l'utilisabilité et l'appropriation d'iTeachApp par les enseignants. L'expérimentation consistait à donner aux enseignants qui le souhaitaient un accès à iTeachApp afin de la tester pendant une période définie, puis d'effectuer une étude quantitative sur la base des traces d'activité de la plateforme, et de réaliser une étude qualitative à travers un ques-

tionnaire envoyé aux enseignants afin de recueillir leurs retours et suggestions. Ceux-ci ont révélé un intérêt considérable pour notre modèle comportemental, les indicateurs de TA et les systèmes de recommandation. Certains axes ont été d'avantage privilégiés par les enseignants qui ont indiqué que leur choix était fondé sur la nature de leurs cours. En ce qui concerne nos indicateurs, la tendance d'utilisation du LMS semble être l'indicateur le plus pertinent pour eux car il leur permet de voir leur utilisation globale des différentes fonctionnalités de l'axe du modèle choisi. Cependant, cette expérimentation a fait apparaître un manque de compréhension par les enseignants des différents termes que nous avons utilisés, notamment ceux utilisés pour qualifier les deux autres indicateurs. De plus, nous avons identifié une limitation liée aux recommandations de fonctionnalités non utilisées. En effet, le système peut suggérer des fonctionnalités que l'enseignant connaît déjà mais qu'il ne souhaite pas utiliser. Ces fonctionnalités peuvent ne pas être adaptées aux cours de l'enseignant et/ou à son style d'enseignement, etc. Par ailleurs, cette expérimentation a également permis de dégager des pistes pour améliorer notre application et nos propositions (modèle, indicateurs et recommandations).

Les recherches que nous avons menées tout au long de cette thèse présentent plusieurs limites. Par exemple, de nombreux enseignants utilisent d'autres outils que le LMS pour gérer leur enseignement auxquels nous n'avons pas accès. De plus, notre étude ne prend pas en compte les activités d'ensei-

gnement en présentiel et nous considérons l'ensemble des enseignants de la même manière. En effet, nous ne tenons pas compte du contexte (par exemple : les domaines enseignés et niveaux universitaires, etc.) et la prise en compte de ces derniers pourrait offrir des profils plus fins. Enfin, une partie de notre ensemble de données concerne la période du confinement causé par le COVID ce qui peut provoquer un changement de contexte.

En revanche, les réflexions menées au cours de ce travail de thèse ouvrent de nombreuses perspectives. Tout d'abord, nous avons l'intention d'affiner notre modèle avec l'inclusion et l'analyse de nouvelles caractéristiques qui permettraient de consolider nos axes et pourraient également fournir de nouveaux axes. En ce qui concerne iTeachApp, nous projetons évidemment d'étudier l'impact que cette application pourrait avoir sur la pratique des enseignants. Nous avons également l'intention d'expérimenter notre application dans d'autres universités en France. En outre, la maîtrise d'un LMS ne se limite pas à la maîtrise de ses fonctionnalités, une bonne adaptation pédagogique est également nécessaire. Les enseignants doivent concevoir avec précision leurs scénarios pédagogiques afin de les adapter à l'outil numérique. Ce travail peut donc initier de nombreuses réflexions liées à la maîtrise de la technologie au service de la pédagogie. Par exemple, assister les enseignants dans leur conception pédagogique au sein des LMS est une voie intéressante à explorer.

Title: Teaching analytics: support for the evaluation and assistance in the design of teaching through artificial intelligence

Keywords: teaching analytics, learning Management System, self-evaluation, data analysis, clustering, recommendation

Abstract: The present thesis is focused on the use of Teaching Analytics to analyze teachers' behaviors and assist them in using Learning Management Systems (LMS). Teaching Analytics (TA) refers to methods and tools to help teachers to analyze and improve their pedagogical designs, and more recently, to analyze the way they deliver their lessons. Our goal is to exploit this area of Teaching Analytics to help teachers to evaluate their behavior on their institutional LMS. In fine, we aim at providing teachers with personal and social awareness tools, allowing them to engage in learning situations that aim at improving their use of the LMS, and to support these situations with automatic feedback and peer learning.

To achieve this goal, we designed an evaluation model based on (i) a qualitative analysis from interviews we had with several pedagogical engineers and (ii) a quantitative analysis we conducted on three years of teachers' activities on the University's LMS. The behavioral model we designed describes teachers' practices on the LMS through six major axes: evaluation, reflection, communication, resources, collaboration, as well as interactivity and gamification.

Thereafter, we defined two TA metrics : LMS usage trend and usage scores. The first one allows us to find groups of teachers with a particular usage according to each axis (intensive usage, non-intensive usage). To complete the results of the latter indicator, we propose usage scores. We have therefore proposed two scores to express particularities of use such as curiosity or homogeneity of each

teacher in order to provide a rich support for self-evaluation.

We also proposed 3 recommender systems to help teachers to improve their practices in the university's LMS. A first recommendation system allows to propose features not used by the teacher according to each axis in order to motivate them to discover these functionalities and to help them to improve the design of their courses. A second simple recommender system has been proposed to facilitate teachers' contact with pedagogical engineers in case of need. Finally, a hybrid recommender system was developed to allow teachers to receive recommendations from their peers. The last phase of our methodology consists in instrumentalizing the obtained results, through a user-centered approach, in a support tool named iTeachApp that includes dashboards allowing to visualize information on teachers' behavior and recommendations.

iTeachApp is a web application dedicated to teachers and pedagogical engineers to (i) provide the former with self-assessment and recommendation functionalities, and (ii) allow the latter to detect teachers with specific needs and teachers with an expert profile. It has been experimented at our university to study its usability, utility and appropriation by teachers. The results showed that teachers were interested in adopting iTeachApp and found our proposals relevant. However, this experimentation revealed a lack of understanding of various terms we used. At the same time, it provided insights to improve our application and proposals (model, indicators and recommendations).