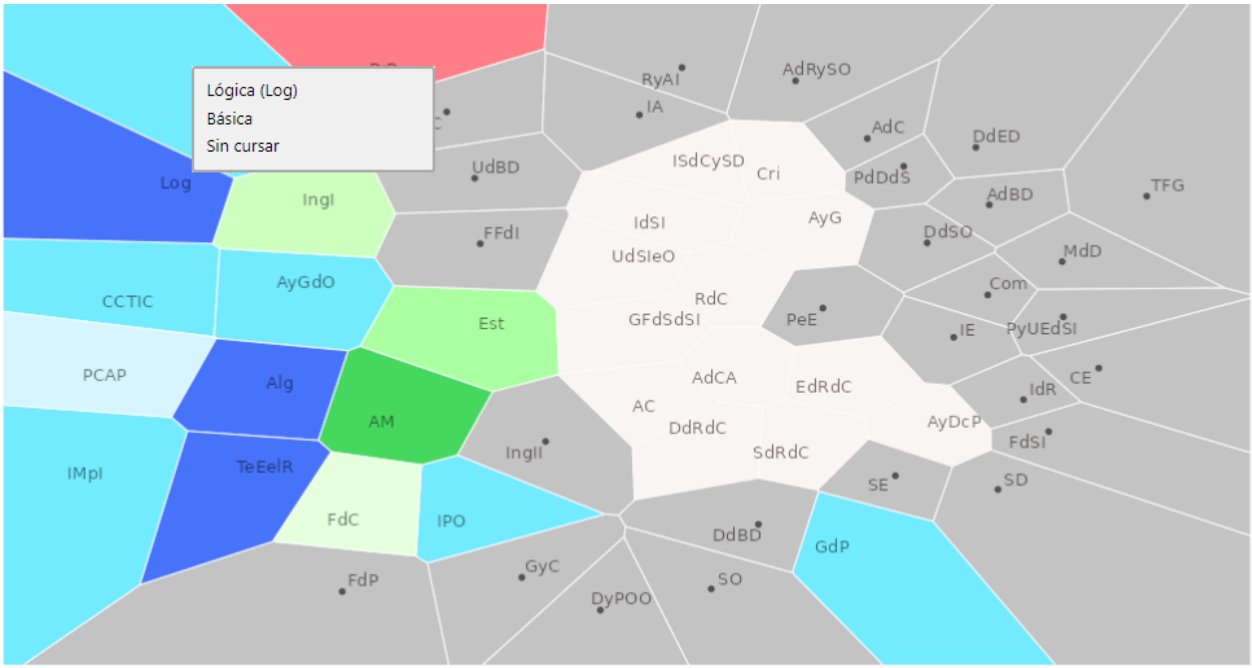

An enrollment dashboard to enhance decision making for students and advisors

Noe Rivas

Thesis Directors:
Dr. Julià Minguillón Alfonso
Dr. Jonathan Chacón Pérez

Universitat Oberta de Catalunya

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Lastly, this thesis is dedicated to my son, Martí.

Abstract

In open and online universities, students have a certain degree of flexibility when choosing their academic paths, often navigating through a complex and overwhelming amount of information. While this flexibility is generally seen as an advantage, it can also lead to poor enrollment decisions, student frustration, and increased dropout rates. This thesis addresses the critical challenge of enrollment decision making in flexible higher education, by designing and evaluating a recommendation system integrated within a learning dashboard prototype for students and advisors taking the Computer Science degree at the Universitat Oberta de Catalunya (UOC).

This research investigates students' and advisors' information needs during enrollment to develop a technological solution that enhances decision making. Specifically, the study explores whether a recommendation system integrated within a learning dashboard can support subject selection and academic planning during the enrollment process.

A design and creation research methodology was adopted, combining both qualitative and quantitative methods. Data collection techniques included web analytics, questionnaires, user interviews, simulations, and heuristic evaluations. An iterative design approach informed the development of the dashboard prototype. The prototype, tailored for students and their advisors, features an interactive curriculum map, personalized subject recommendations, and a semester calendar visualization. The development process involved multiple phases: identifying student needs, defining design requirements, implementing a recommendation system using enrollment data, and refining dashboard usability through questionnaires, interviews and expert evaluations.

Prototype validation, involving both students and advisors, confirmed the system's effectiveness in improving access to academic information, supporting strategic subject selection, and enhancing enrollment decision making. The findings confirm the relevance of tailored, data-informed learning dashboards for enrollment processes in open and online universities. The prototype not only aligns with student preferences for interactive and transparent tools, but also assists their advisors in their guidance. Despite certain limitations, including the study's focus on a single institution and program, the results suggest broader implications for designing support systems in flexible higher education.

This thesis contributes to the growing field of educational technology by demonstrating how user-centered design, informed by learning analytics and grounded in real institutional data, can be applied to build meaningful decision-support tools for academic advising.

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Chapter 1
Introduction

STEM (Science, Technology, Engineering and Mathematics) higher education plays a critical role in the development of future societies and economies. By equipping students with the knowledge and skills needed to solve complex, real-world problems, STEM education provides innovation and technological advancement. As industries increasingly rely on cutting-edge technologies, a strong STEM knowledge base ensures that individuals can contribute to sectors ranging from healthcare and environmental science to AI and renewable energy. Moreover, STEM education promotes essential abilities that are essential for engaging with a rapidly evolving technological context, such as critical thinking, creativity and collaboration. In an era where digital transformation and sustainability are top priorities, investing in STEM education not only provides economic growth but also prepares the next generation to address some of the world's most pressing challenges. These knowledge needs have resulted in a constant increase in the number of computer science students, with the total almost doubling since 2012. A parallel trend is evident in the number of students choosing to study this field remotely (Ministerio de Ciencia, Innovación y Universidades, n.d.).

Some of the students aspiring to study Computer Science, enroll in an open university, searching for the flexibility of online learning. Open universities typically feature more adaptable educational systems, enabling students to engage in a more personalized and self-directed enrollment process. This adaptability allows students to reconcile their studies with other responsibilities, such as employment or family commitments. Regardless of whether a student undertakes the degree on a full-time or part-time basis, a primary decision involves determining the study pace. Students also need to decide on their learning structure, choosing between a conventional subject load or a more modular approach by completing individual subjects at their own pace. Another crucial decision concerns the selection of a predefined academic itinerary or the customization of their degree. For instance, universities provide a variety of electives and specializations within Computer Science, such as software development or information systems, which can significantly change their future career trajectory.

Therefore, enrollment is the primary decision a student must make each semester, requiring a balance between academic progression through the curriculum, personal interests, and alignment with their professional and personal lives. This flexible enrollment process is critical, as inappropriate subject selections can lead to frustration, failure and potential dropout.

This thesis addresses the challenges of enrollment decision making in flexible higher education by investigating the key information needs of students and strategies for the effective presentation of information to support enrollment decisions. More specifically, this research assesses the relevance of a learning dashboard with a recommendation system for students and advisors in an open university Computer Science degree. In the following Section 1.1, the statement of the problem is introduced. We will explore the challenges faced by students in the enrollment process of open and online universities. A brief summary of previous research within the field of recommendation systems and data visualization in educational contexts and its limitations will be presented, along with the specific issue of enrollment decision making. Our main goal is to develop a learning dashboard that can help students make informed decisions and improve their academic journey. By combining web analysis, user experience design, web development and data visualization, this research aims to find out student's educational needs, properly showcase information and investigate whether learning dashboards and recommendation systems can impact the enrollment processes in open and online universities. The main challenges of this thesis are presented in Section 1.2 including the research questions and objectives. Finally, the organization of this thesis is presented in Section 1.3.

1.1 Statement of the problem

I started my degree at a university for the first time in 2003. During that period, higher education institutions provided students with manuals containing extensive lists of subjects, credit details, descriptions and schedules. It was our responsibility as students to choose subjects wisely, considering our prior knowledge, the timetable and other personal factors. The university enrollment process was time-consuming and required significant effort. Despite thorough examination of all the available information, there was still a possibility of timetable overlapping or enrolling in subjects for which some students were not adequately prepared. Since then, although the Internet revolutionized the search for information, certain challenges persist. Subject selection is still a difficult process; enrollment information might be easier to find, but it is presented in the same old textual and list formats, and subject deadline calendars are usually not available through university websites. Those printed manuals have been changed to online websites, however information continues to be predominantly presented in static formats, lacking the dynamic and interactive elements that could enhance the enrollment experience.

The rise of technology has significantly transformed education, with the Internet playing an important role. This has led to a surge in online educational websites and technology-based learning scenarios (Wallace, 2003). Traditional brick-and-mortar universities began to offer online programs and subjects and fully online universities emerged as a viable alternative to traditional on-campus education (Kim & Bonk, 2006). This change offers numerous benefits. Students enjoy flexibility in time and location, access to vast information resources, potential cost savings and the ability to learn at their own pace (Laurillard, 2005; Arkorful & Abaidoo, 2015). This new approach has allowed non-traditional students to pursue their educational careers while managing work and personal commitments. Distance education or distance learning has evolved over the past two centuries, from basic correspondence to online learning (Moore et al., 2011). Distance learning reflects the ongoing focus on overcoming geographical challenges and using technology to enhance the learning experience. Key characteristics include accessibility, flexibility and diverse interaction possibilities. Online learning generally represents a more advanced and accessible form of distance education (Moore et al., 2011). The adoption of information technologies presented an opportunity to enhance the quality and effectiveness of distance learning by developing online platforms and processes (Beller & Or, 1998), even transforming institutions from distance education to online education (Mason, 2000).

The Universitat Oberta de Catalunya (UOC) is a very good example of an open online university. UOC's educational model allows students to take an active role in their learning, offering flexible programs that align with European Higher Education Area (EHEA) standards. Students can select subjects and tailor their study pace to accommodate their individual needs and commitments, often extending their degree completion beyond the traditional eight-semester time frame. This flexibility is characteristic of many open universities worldwide. A substantial portion of the UOC student population integrates academic and professional efforts. The accessibility and flexibility afforded by open and online education have undeniably enabled these students to undertake their studies while optimizing their available time.

In such a flexible scenario, students can decide how many and which subjects to enroll in, and define their own path within the degree, organizing their time as best suits them. In this way, they can adapt their learning to their available time and decide what workload they may face each semester. This leads to a wide range of options and, therefore, a diverse range of enrollment choices. For instance, at UOC, in the semester 2019/1, more than 37,000 students took at least one subject from one official degree, from a catalog of almost 1,800 subjects scattered among 28 degrees (in two different languages). Most of these 37,000 students enrolled into one and up to five different subjects, generating more than 24,000 different enrollment patterns following a long-tail distribution, where most enrollment patterns were only taken by just one student (Rivas et al., 2021). Some of these enrollment patterns were completely questionable from an academic point of view, and should have been avoided or, at least, students should have been warned.

Figure 1.1 - Example of Computer Science Degree Curriculum

Table with subjects listed in the Landing Page of the Computer Science Degree Curriculum (Spanish Version, 2019). Note that the current URL may no longer be valid due to website updates (Grado Online En Ingeniería Informática | UOC, n.d.).

Asignaturas

Tipología

Primera Matrícula

Semestres

Itinerarios

Formación básica (60 ECTS)	Créditos
Fundamentos de programación	6
Prácticas de programación	6
Administración y gestión de organizaciones	6
Álgebra	6
Análisis matemático	6
Lógica	6
Estadística	6
Trabajo en equipo en la red	6
Fundamentos de computadores	6
Fundamentos físicos de la informática	6

This flexibility of open universities, while offering numerous advantages, also presents unique challenges and it has generated several problems, such as high dropout rates (Wladis et al., 2014). An inadequate enrollment can lead to the failure of one or several subjects, frustration and even the total abandonment of the degree by the student (Meyer & Marx, 2014). Previous research highlights the importance of student characteristics, subject design, institutional support, and environmental factors in student success and dropout rates (Lee & Choi, 2011; Grau-Valldosera et al., 2019). To address these factors, institutions can implement strategies such as personalized support, effective subject design and a supportive learning environment (Wladis et al., 2017; González et al., 2018). By considering factors such as subject structure, workload and student support, institutions can implement strategies to enhance student engagement and reduce dropout rates (Bawa, 2016). In this sense, careful subject selection and academic planning are crucial to ensure student success.

Nevertheless, institutional web pages still present information as text and lists or tables, as shown in Figure 1.1. These lists may contain information that is not sufficient for the subject selection process, or content that was created from the perspective of the institution rather than the end stakeholders (Scott & Savage, 2022). Students may find it challenging to sort through an overwhelming amount of information or may even find it insufficient to plan and select subjects strategically (Scott & Savage, 2022; Stevens et al., 2018). Although students can find more information online and access it more quickly thanks to the Internet in practice, they often encounter a vast amount of information during enrollment, making it challenging to navigate or even locate the relevant details (Chang et al., 2016; Iatrellis et al., 2017). Consequently, they may find it difficult to select the subjects that best suit them that semester. It is well known that informal student networks function as supplementary infrastructures for the circulation of academic information, often addressing gaps in the university's official communication (Morosanu et al., 2010).

Advisors play a partial role in mitigating students' inability to access the correct information. A good advising process can be time-consuming, so automating or providing tools for some of the advisor's tasks can optimize this process (Feghali et al., 2011). Regarding students' advising needs, previous research suggests that students require support with the following: the enrollment system, information about subjects, assistance in enhancing study skills, aid with academic matters and guidance in career-related issues (Chan et al., 2019). Furthermore, there is plenty of data generated by institutions that is not accessible to students or even their advisors. For instance, students might need additional information about subjects such as assessment type, the number and workload of assignments, other students' opinions about the subjects, etc. However, universities usually provide only a brief subject description, and sometimes even advisors do not have this kind of additional information (Khalil & Williamson, 2014). Moreover, the student-advisor communication process is considered a crucial factor by many researchers (Irani et al., 2014). Beyond email, dedicated dialogue spaces are needed to enhance student-advisor communication and address students' guidance requirements throughout the enrollment process, which current institutional information sources often fail to fully satisfy.

Academic advising systems aim to address a range of core advising tasks, with subject selection being the most recurrent. Be that as it may, other tasks are also important, such as academic program planning, student-advisor communication, academic scheduling, student performance monitoring, retention efforts, providing information and solving other questions (Assiri et al., 2020). Daramola et al. (2014) developed a multi-agent system to provide personalized guidance for students in programming language subjects. In Ganeshan and Li (2015) a web-based intelligent advising system utilizing collaborative filtering was developed to offer personalized subject recommendations. In Eckroth and Anderson (2019), a subject advising system that uses a planning engine to develop multi-year subject schedules for complex scenarios was developed. Another notable example of an academic advising system is LADA, a learning analytics dashboard designed to enhance advisor decision making (Gutiérrez et al., 2020). This tool offers a range of functionalities, including a comprehensive overview of student performance, subject selection tools and visualizations of complex data. In summary, within the field of academic advising systems, two types of systems emerge: recommendation systems and learning dashboards.

The use of a recommendation system represents a logical approach in order to enhance advising procedures. These systems are designed to function as a complement to, not a substitute for, human advisors. Recommendation systems are software applications that suggest items to users based on their preferences and behavior (Aggarwal, 2016). By understanding individual preferences, recommendation systems can offer personalized suggestions, enhancing user experience and driving engagement across various topics such as: movies, music, books, online education, business, web search, social networks, etc (Park et al., 2012; Behera & Nain, 2023). In the case of higher education, learning recommendation systems have emerged as a significant research area in e-learning (George & Lal, 2019; Urdaneta-Ponte et al., 2021; Bin et al., 2024), with applications ranging from predicting student performance to informing academic advising. By anticipating student needs and providing personalized guidance, these systems can contribute to improve student retention and success (V. Maphosa & Maphosa, 2023). Notwithstanding, traditional recommendation systems, commonly employed in e-commerce and other fields, cannot be directly applied to online learning without significant adaptations (Zaiane, 2002; George & Lal, 2019). Hybrid approaches combining traditional recommendation systems and context information seem to be the best way to address the particularities of flexible enrollment. For instance, in Gulzar et al. (2018) a hybrid recommendation system designed to assist students in subject selection is introduced. The system provides personalized subject recommendations aligned with individual student needs and goals. Ibrahim et al. (2019) proposes an ontology-based hybrid recommendation system to assist students in selecting suitable university subjects. By combining collaborative and content-based filtering with ontology mapping, the system offers personalized recommendations aligned with student goals and career aspirations. In Castells et al. (2020) the authors describe a system that takes historical academic data and allows students to select subjects and predict their performance, but using classical tables and line charts as a visualization. In Wagner et al. (2024) a subject recommendation system targeting at-risk students is presented. The system uses student performance data and employs explainable k-nearest neighbor algorithms to offer personalized subject recommendations, demonstrating potential to improve student success and retention rates. A specific review of recommendation systems for choosing elective subjects identified emerging trends that needed further investigation to enhance their effectiveness. Key areas for exploration include the integration of acceptance models to improve recommendation adoption and the analysis of user feedback (M. Maphosa et al., 2020). The state of the art research can be found in Chapter 2, Section 3.

As an example, a significant direction for future research involves addressing the lack of explainability in recommendation systems by prioritizing user understanding and control. In this regard, learning analytics dashboards have emerged as interesting tools for visualizing educational data and supporting informed decision making. By using data from various sources, these dashboards provide valuable insights into student performance, engagement and learning patterns. For example, Olmos and Corrin (2012) explain the iterative design process used in developing a learning analytics reporting system, demonstrating the value of continuous refinement and user-centered evaluation. Another example is GLASS, a web-based platform that facilitates learning analytics by visualizing user interactions and providing valuable insights. Its modular architecture and customizable features allow users to explore data and gain deeper understanding of learning processes. Chou et al. (2017) introduces an approach to develop curriculum-level open student models. By analyzing subject enrollment data and student performance, the system provides valuable insights into student core competencies and facilitates self-reflection. Another remarkable example, with a novel approach, is CourseQ, an interactive subject recommendation system developed by Ma et al. (2021). This system utilizes a visual interface for subject exploration, aiming to enhance the transparency and user satisfaction associated with subject recommendations. The dashboard achieves this by providing students and advisors with an overview of their progress, thereby facilitating informed decision making. Key challenges in developing effective learning dashboards include identifying relevant indicators for diverse user groups, defining meaningful learning outcomes, creating visualizations tailored to educational contexts and further research in the validation processes (Schwendimann et al., 2017). Bodily and Verbert (2017) also highlight key considerations for developing effective educational dashboards, which include: defining system objectives and justifying data selection, creating appropriate visualizations, taking into account user needs, creating intuitive designs, reasoning visualization techniques, taking into account student perceptions and behavioral impacts, and explaining how, when, and why these types of systems are used.

The absence of a singular solution for the presentation of enrollment information requires learning dashboards to be tailored according to the specific attributes of each learning environment. The development of learning dashboards that incorporate recommendation systems applied to higher education scenarios is still a relatively unexplored field of knowledge. Existing dashboards often lack the customization required to meet the specific needs of students and advisors in open and online education. Properly developing a competent project in this field requires a multidisciplinary approach: web analysis, user experience design, web development, recommendation algorithm implementation and data visualization techniques need to be integrated. In this thesis, we will develop a prototype and validate its findings, employing a research methodology based on design and creation (Oates et al., 2006).

Quantitative and qualitative methods will be combined to gain insights: web analytics, questionnaires, simulations, interviews and heuristic evaluations. By creating an iterative design and development process, this research aims to gain a comprehensive understanding of student needs and preferences, properly showcase information to assist students and advisors in their enrollment decision-making processes and examine whether the use of learning dashboards and recommendation systems is relevant for the decisions taken by students and advisors when enrolling.

In summary, this research's primary objective is to investigate the enrollment information needs of students within the context of open and online universities, develop a prototype that effectively addresses these needs and evaluate the prototype's effectiveness through a validation process. While offering valuable insights into the impact of enrollment learning dashboards applied to open higher education, this research is subject to certain limitations. Its findings should be interpreted within the specific context of the UOC's Computer Science degree program. The research is designed to provide an in-depth exploration of this particular case study, which may limit the direct generalizability of the results to other disciplines or institutions. Furthermore, as with all qualitative research, findings may exhibit some degree of subjectivity, influenced by our interpretations as researchers, as well as the inherent limitations of data collection methods. Nevertheless, other quantitative research methods have been performed to mitigate this. It is also important to clarify that the research focus is not on delivering immediate, ready-made solutions to the UOC's enrollment challenges. While the prototype evaluation was conducted with real users, it was a controlled evaluation and did not intervene directly in the live enrollment process. This choice, made for ethical considerations, implies that the full impact of the dashboard on actual enrollment decisions requires an institutional implementation process.

1.2 Research challenges: Questions, objectives and contributions

This research employs a multi-faceted approach to investigate enrollment in open and online higher educational contexts. Firstly, it focuses on identifying the key information needs of students within the context of flexible higher education programs. Specifically, it investigates:

Research Question 1 (RQ1): *Which information is key for students when taking enrollment decisions in higher education official degrees that allow some flexibility?*

By addressing this research question, this study aims to identify key factors that can enhance students' enrollment decision-making process and create a mapping of relevant academic information for the enrollment procedure. This will contribute to a deeper understanding of student information needs and inform the development of more effective enrollment support systems within the open online higher education sector.

Secondly, this research investigates how to effectively present crucial information to support student and advisor decision making during the enrollment process. In particular, it addresses the following:

RQ2: *How can information be appropriately showcased to assist students and advisors in their enrollment decision-making processes?*

By addressing this research question, this study aims to develop an effective representation of enrollment-related data, enabling both students and advisors to access relevant information pertaining to the enrollment process. This objective will be achieved through the creation of an interactive learning dashboard integrated with a recommendation system specifically designed to support the enrollment procedure. Ultimately, this research will contribute to the development of a user-centered learning dashboard incorporating a recommendation system, potentially enhancing the enrollment experience for both students and advisors within the open online higher education sector, such as the UOC.

Finally, this research investigates the relevance and impact of learning dashboards integrated with recommendation systems in supporting student and advisor decision making during the enrollment process. Precisely, it addresses the following:

RQ3: *To what extent is the use of a learning dashboard with a recommendation system relevant for the decisions taken by students and advisors when enrolling?*

By addressing this research question, this study aims to analyze the impact of learning dashboards and recommendation systems on the enrollment process from the perspectives of both students and advisors. This will involve an evaluation of integrating these technologies into the enrollment process to provide evidence on their effectiveness in supporting informed decision making within the open and online higher education enrollment context. The findings of this research will contribute to a better understanding of the potential benefits and limitations of utilizing learning dashboards and recommendation systems to enhance the student and advisor enrollment experience.

1.3 Thesis organization

This thesis is divided into seven chapters, each addressing a distinct aspect of the research. This section provides a brief overview of the content and objectives of each chapter, presenting the progression of the argument and the contribution of each part to the overall study.

Chapter 2: State of the art provides a comprehensive review of the relevant literature. It begins by examining the current educational context, specifically focusing on the challenges and opportunities presented by open and online learning environments. This is followed by an exploration of the role of academic advising in supporting student success. The chapter then presents the existing literature on recommendation systems, exploring different approaches and their applications in educational settings. Subsequently, it examines the existing research on educational learning dashboards, analyzing their functionalities, limitations, evaluations and potential for supporting student learning and decision making. Finally, a summary of the key findings and research gaps identified in the literature review is presented.

Chapter 3: Research methodology describes the methodological approach adopted in this research. It details the research process, including the selection of the target population (students enrolled in the UOC Computer Science degree), the ethical considerations and data collection procedures. This chapter also discusses the limitations of the study, acknowledging potential biases and the scope of the research findings.

Chapter 4: Students' information needs presents the findings from the initial data collection phase. It begins with an overview of the UOC enrollment process, followed by an analysis of the Web Analysis conducted on user interactions with the UOC website. The chapter then presents the results of the two-stage student questionnaire, analyzing the key information needs identified by students during the enrollment process.

Chapter 5: Learning dashboard development describes the iterative process of developing the learning dashboard prototype. It outlines the initial design proposals, the integration of the recommendation system, the development of the interactive map and subject recommendation functionalities and the simulation of student enrollments. The chapter also details the development and refinement of the prototype based on feedback from students and advisors through a series of interviews.

Chapter 6: Prototype validation presents the findings of the final validation phase. This chapter analyzes the results of the student and advisor questionnaires, the findings from the interviews conducted and the results of the heuristic evaluation conducted by experts.

Chapter 7: Conclusion summarizes the key findings of the research, discusses the limitations of the study and explores the potential for improvement and future directions for the developed prototype. It also considers the broader implications of the research findings for the design and implementation of innovative support systems for students in open and online learning environments.

Finally, the *Annex* section provides supplementary materials that support the research methodology and findings presented in this thesis. It includes detailed documentation of the instruments and procedures used in data collection and analysis, such as questionnaires administered to students and advisors, interview protocols and consent forms. Furthermore, it contains design prototypes and evaluation tools used in the development and validation of the enrollment dashboard, including initial designs, proof of concept tests, heuristic evaluations and examples of data visualizations.

Chapter 2
State of the art

The Internet has revolutionized traditional educational methods, enabling the development of flexible and accessible online education (Wallace, 2003; Laurillard, 2005; Arkorful & Abaidoo, 2015). Students with diverse abilities, interests and time commitments are able to access programs that can be adapted to their individual needs: demanding a flexible pace and a high degree of student autonomy in decision making. At the same time, advances in technology have made it possible to capture and analyze all interactions within digital learning environments, providing new insights by means of a wide amount of available data. This shift has led to the emergence of learning analytics, a field that uses data gathered in educational scenarios to improve teaching and learning outcomes (Siemens, 2013). The gathered data has the potential to inform and enhance learning processes at any stage of the educational process, from enrollment to graduation.

In the context of open and online universities, students enjoy a greater level of flexibility. Nevertheless, they often face unique challenges, beginning with the enrollment process. Due to the open nature of the open enrolment process, which allows students to enroll in subjects in any order they choose, a series of challenges arise such as: navigating complex degree structures and making informed decisions about subject selection. To address these challenges, institutions have increasingly turned to technology-based solutions, improving academic advising by means of recommendation systems and educational learning dashboards, amongst others. Interactive data visualization applied to education is also becoming an interesting approach to explore and interpret learning analytics data.

This chapter examines the role of different tools and strategies in supporting students and advisors during the enrollment process in open and online universities with a high level of flexibility. We review the potential benefits of online academic advising, the effectiveness of recommendation systems in suggesting relevant subjects and the value of learning dashboards in visualizing enrollment-related information. By understanding the impact of these technologies, we can identify opportunities for enhancing the enrollment experience for students in online and open learning environments.

2.1 Educational context

The field of education significantly changed as technology became increasingly integrated into teaching and learning practices. In particular, it benefited from the development of Internet-related technologies. The result was an incredible increase in the number of online educational websites and technology-based educational scenarios (Wallace, 2003). In particular, traditional brick-and-mortar universities began to offer online programs and subjects and fully online universities emerged as a viable alternative to traditional on-campus education (Kim & Bonk, 2006). Therefore, the way universities offer their degrees and subjects has changed. Some of these changes have brought substantial benefits, such as flexibility in time and location for studying, access to countless sources of information, cost savings in education and enabling students to study at their own pace (Laurillard, 2005; Arkorful & Abaidoo, 2015). This new way of conceiving education allowed many non-traditional students to access new degrees and subjects, as they were able to adapt it to the reality of their day-to-day tasks. Therefore, students' profiles and needs have also become very diversified.

Distance education, also known as distance learning, is an educational field where students and teachers are separated by physical distance, utilizing both traditional and online educational scenarios. Distance education has evolved significantly over nearly two centuries, from print-based correspondence to the emergence of interactive online learning environments. Heydenrych and Prinsloo (2010) detailed the gradual shift from traditional, text-based instruction to contemporary models characterized by the integration of technology, multimedia and interactive learning experiences. While the definitions of distance education and distance learning have evolved over time, the underlying principles of instruction across distances remain consistent. The focus has shifted from overcoming the limitations of physical distance to using technology to enhance the learning experience.

One of the biggest advantages of distance education is the flexibility it provides. Students can learn from anywhere in the world, at their own pace, and on their own schedule (Sadeghi, 2019). This makes it ideal for busy professionals, parents, or anyone with geographical limitations. Distance learning can also be significantly more affordable, as without the costs of commuting, housing, and on-campus fees, distance education programs can be a more economical option, although this does not have to apply to all educational contexts and situations (Xu & Xu, 2019). Finally, distance learning allows students to continue working full-time while pursuing their education part-time, avoiding the financial burden of taking time off (Sadeghi, 2019). The concept of flexibility is, therefore, crucial for student success.

Nowadays, in higher educational contexts, the term 'distance education' is largely synonymous with 'online learning', as the vast majority of distance learning programs are now delivered through digital platforms and technologies. In fact, there is a consensus that online learning offers a more advanced and accessible form of distance education (Moore et al., 2011). The adoption of information technologies presented an opportunity to enhance the quality and effectiveness of distance learning by developing online platforms and processes (Beller & Or, 1998), even transforming institutions from distance education to online education (Mason, 2000).

Nevertheless, online learning is also a multifaceted concept with various definitions. While some define it as a distinct mode of education, others view it as an evolution of distance learning, emphasizing the increased use of technology (Conrad, 2002; Hiltz & Turoff, 2005; Moore et al., 2011). Key characteristics of online learning include accessibility, flexibility, and the potential for diverse interactions. While some authors highlight the technological aspects of online learning, others focus on its ability to provide educational opportunities for students that could not access education otherwise (Conrad, 2002; Lowenthal et al., 2009; Moore et al., 2011). Online learning has evolved significantly, incorporating different technologies such as video conferencing, computer-assisted instruction, multimedia materials, interactive simulations, asynchronous learning networks, collaborative learning platforms and virtual learning environments (Hiltz & Turoff, 2005), offering a compelling alternative to traditional on-campus education. To maintain consistency and clarity, this research will employ the term ‘online learning’ to refer to ‘distance education’, recognizing the significant overlap between these two concepts in the current educational landscape.

At the same time, online learning and open universities are closely intertwined. Open universities, designed to be accessible to a wide range of students with more flexible admission and retention criteria, often rely heavily on online learning methodologies. These institutions frequently offer flexible subject formats, online resources, and support services that enable students to learn at their own pace and from any location. Moreover, open universities offer students a greater degree of flexibility in terms of subject selection and scheduling, allowing them to achieve their academic goals in a way that best suits their individual needs and circumstances. However, it is important to acknowledge that online learning is not perfect for everyone. The absence of face-to-face interaction and the potential for distractions can be considered disadvantages of online learning (Sadeghi, 2019). Therefore, to effectively support student learning in online environments, educational systems must prioritize the creation of spaces for meaningful dialogue and interaction among students and other stakeholders.

A particular example of an open online university is the Universitat Oberta de Catalunya (UOC). This institution, established in 1994, stands as a pioneering institution in the field of online and open education. Since its creation, the UOC has been dedicated to breaking down barriers to higher education, making its programs accessible to a diverse student population. UOC’s educational model empowers students to take an active role in their education, encouraging a collaborative and engaging learning environment. UOC offers officially recognized university degrees that align with the European Higher Education Area (EHEA) standards. These programs typically require 240 ECTS credits and can be completed in eight semesters of full-time study. Nevertheless, the UOC's educational model allows students to choose their preferred subjects and pace of study, providing a personalized educational experience (Sangrà, 2002). Therefore, students can select subjects independently, without being constrained by specific semesters or prerequisites (except in some cases). Students often enroll in two or three subjects per semester, extending the degree completion time well beyond the expected eight semesters. This flexibility allows students to tailor their academic journey to their individual needs, as it is quite common for them to balance their work and family commitments with their studies. While the term 'open' may have diverse interpretations across universities, it consistently emphasizes flexibility in learning. While institutions provide choice, students need autonomous and self-regulated learning skills. Therefore, students must possess the ability to effectively manage their learning when presented with options regarding time, pace, and content (Per et al., 2012). Making the right decisions is, consequently, crucial for their development.

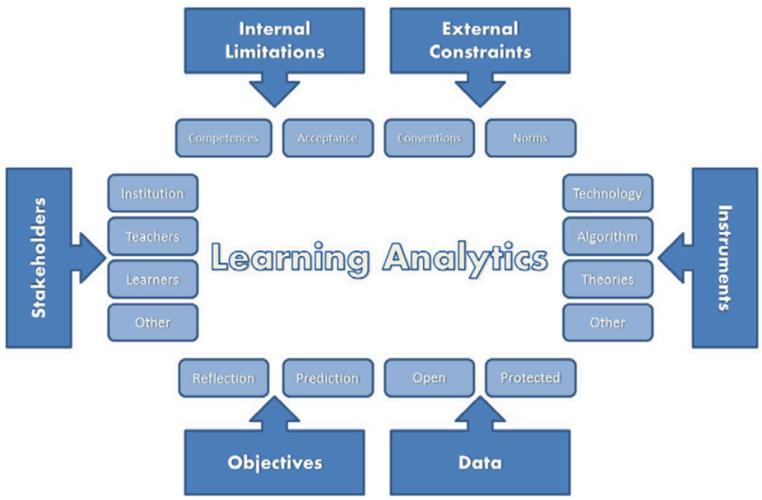
Despite the numerous advantages associated with online education, students may perceive a lack of communication and support, feel that they are not fully experiencing the graduate student journey, or even experience isolation (Irani et al., 2014). Consequently, many universities have incorporated communication tools to enhance engagement processes in online education. Although technology plays a significant role in facilitating some processes, a human element, such as advisors, is necessary to provide personalized support and ensure a positive educational experience (Cross, 2018). Some of the most common communication methods include email, discussion forums, chat rooms, and other web applications (Ortiz-Rodríguez et al., 2005). This integration of technology into educational processes has brought about changes for both students and faculty members, who have had to make efforts to implement and embrace it (Irani et al., 2014). However, in some instances, these tools have not been utilized effectively, impacting students' perception of the quality of online education. In fact, some studies recommend investing in quality communication and technical support tools and encouraging educational leaders to acquire skills and methods in online education that facilitate communication and feedback (Ortiz-Rodríguez et al., 2005). For students to feel motivated and comfortable, communication and interaction between faculty, advisors, and students are crucial (Ortiz-Rodríguez et al., 2005; Cross, 2018). Support systems, such as online orientation and advising, centralized information access, and regular communication outside the academic setting, also benefit students pursuing their studies online. In this regard, assessing tools employed in online education related to communication, quality and support to enhance the quality of online experiences and alleviate the sense of isolation felt by students is an interesting research line (Irani et al., 2014).

In parallel, the use of such fully equipped virtual learning environments in higher education institutions allows students and teachers to interact with their peers, digital resources and services anytime and from anywhere. These interactions generate a vast amount of data that can be collected, analyzed and visualized to gain a deeper understanding of student behavior. When students engage with digital services, resources and other users in a virtual learning environment, they leave behind a digital trace that can be captured and stored for further analysis, using relevant evidence-based data. Researchers have long recognized the potential value of this data and the concept of learning analytics (or previously named, educational data mining) has emerged as a natural progression from a data-based perspective to an intervention-based one, with the aim of studying how to analyze, understand and improve technology-enhanced learning scenarios (Siemens, 2013). Beyond educational data mining, learning analytics has experienced a surge in popularity, as evidenced by the increasing number of publications in educational technology journals and conferences (Banihashem et al., 2018).

Learning analytics aims to study the way technology is used in order to improve teaching and learning, not just analyzing what happens in a virtual learning environment. In essence, this discipline uses data as well as statistical and computational methods to understand and enhance the learning experience of students and other educational processes such as teacher interventions and administrative monitoring. It is a rather multidisciplinary field that integrates a wide range of disciplines such as education, e-learning and computer and data science (Siemens, 2013). The goal of learning analytics is to use this data to identify patterns and trends that can improve decision making, student outcomes and further develop educational interventions and educational programs. Greller and Drachsler (2012) identify six essential dimensions for successful learning analytics: stakeholders, objectives, data, instruments, external limitations and internal limitations, as shown in Figure 2.1. These factors highlight the need for a comprehensive approach that addresses both technical and organizational aspects. Technical challenges might include data access, preparation and analysis, while organizational challenges involve cross-departmental collaboration and cultural change. To overcome these obstacles, institutions need to invest in integrated systems and foster a data-driven culture.

Figure 2.1 - Dimensions of Learning Analytics

Critical dimensions of learning analytics. Proposed design framework for learning analytics by (Greller & Drachsler, 2012).



Learning analytics utilizes data from a variety of stakeholders, such as students, teachers, advisors and other educational participants' interactions with digital resources and services. Stakeholders in learning analytics can be categorized as data clients and data subjects (Greller & Drachsler, 2012). Data clients are those who benefit from the analytics process and use its outcomes to inform their actions. Data subjects are the individuals who provide the data, typically through their online interactions and behaviors. In some cases, data clients and data subjects may be the same, as when learning analytics provide students with personalized feedback rather than solely informing teachers. Learning analytics offers a range of valuable applications for various stakeholders. Some examples include:

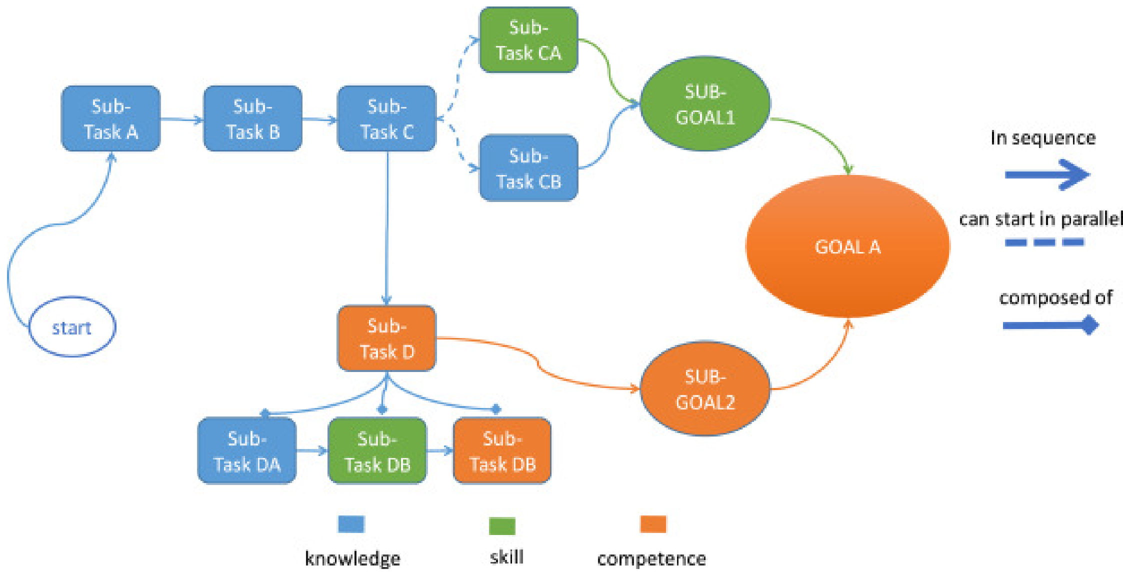
- **Student support:** Personalized feedback, learning resource recommendations and peer connections.
- **Teacher insights:** Identification of knowledge gaps and analysis of group dynamics for improved instruction.
- **Institutional evaluation:** Tracking of student performance to inform program improvements.
- **Stakeholder alignment:** Addressing the needs of diverse stakeholders in formal, non-formal and work-based learning environments.

Despite the potential benefits of learning analytics, its implementation in large-scale online distance learning institutions presents several challenges (Prinsloo et al., 2012). These include navigating complex degree structures, data overload, a lack of conceptual understanding, conflicting institutional goals and the difficulty of developing tailored support systems for diverse student populations. Gathering, organizing and storing data is crucial for providing researchers and practitioners with access to a unified learning analytics database, also known as Learning Record Store (Minguillón et al., 2018). The learning record store captures data from a virtual learning environment using a standardized model and stores it in a cloud-based infrastructure, mainly due to the huge amount of data gathered. Data can be used for various research and analysis purposes, including addressing challenges like dropout, engagement and automated feedback. The learning record store offers a valuable resource for institutions to enhance their understanding of teaching and learning processes and inform evidence-based decision making.

Nevertheless, institutional data requires not only processing but also being translated into meaningful interpretations for stakeholder-specific applications. In this sense, data visualization uses the graphical representation of data, by means of charts, graphs, or other visuals, to make complex information easier to understand for a bigger audience, not only domain experts. It helps to identify patterns, trends, and insights that might be hidden in raw data. By effectively communicating data, it enhances decision making and reveals hidden insights. Unfortunately, common visualization techniques only include bar charts, line charts, pie charts, scatter plots, maps and static infographics. While these types of visualizations may not be suitable for complex educational processes, they are commonly employed in learning dashboards. While dashboards are valuable tools, their effectiveness is limited without a comprehensive understanding of user needs and a focus on user-centered design (Alhamadi et al., 2022). Klerkx et al. (2014) explores the use of visualizations in various aspects of the learning process. It discusses how visualizations can improve access to learning materials, aid in understanding complex concepts and improve collaboration among learners. The authors highlight the importance of considering the specific context and learning objectives when selecting and implementing visualization techniques. They also emphasize the need for further research to fully understand the impact of visualizations on student learning outcomes. For instance, Sedrakyan et al. (2019) proposes a visualization framework (conceptual mappings) for guiding visualization representations in learning dashboards, describing processes, not just data as in traditional learning dashboards. In this sense, planning profiles should enable interactive selection of learning goals and present a sequential visualization of the corresponding learning journey, including subgoals, subtasks and prerequisite goals (as shown in Figure 2.2). As mentioned earlier, advancements in computing technology and graphics have provided an abundance of visualization options that makes selecting the most appropriate visualization for a given dataset a critical challenge (Evergreen, 2019). The study links dashboard design principles with learning process and feedback concepts, providing recommendations based on conceptual analysis and empirical evidence. The authors also suggest that future work should focus on empirical evaluation of the framework, prototyping, and expanding the scope of visualizations.

Figure 2.2 - Sample of an interactive learning journey data visualization

A sample interactive learning journey based on a chosen learning goal (Sedrakyan et al., 2019). *The visualization represents a sequence of pre- and post-subgoals within an educational journey, with different goal and task levels categorized as knowledge, skill, and competence.*



Therefore, although plenty of data might be accessible, understanding the appropriate context for visualization and stakeholders' needs is essential. For instance, open universities' flexibility in subject enrollment presents an opportunity to record and visualize these registrations and their later impact on student academic performance. In this sense, the UOC enrollment process offers a flexible and personalized experience. Students can explore program information within the website, seek guidance from advisors and carefully consult individual subjects. While there are some limitations on subject selection, students have significant autonomy in creating their own personalized study plans. Throughout the enrollment process, the UOC provides comprehensive support and resources to assist students in making informed choices and ensuring a smooth transition into their academic studies. However, this diversity can also lead to challenges, as some students may make enrollment choices that do not align with their academic goals or abilities. Such mismatches can contribute to feelings of disengagement and ultimately increase the chance of dropping out. Enrollment flexibility could be seen as another advantage of open and online universities, but it can also contribute to significant challenges. Dropout rates, particularly in the first semester, tend to be higher than traditional universities, partly due to students underestimating the workload and depth of online subjects. Careful subject selection is crucial to mitigate these challenges and ensure student success (Scott & Savage, 2022). Additionally, the high enrollment variability in open universities complicates semester planning on an institutional level, further emphasizing the need for effective analysis and planning strategies.

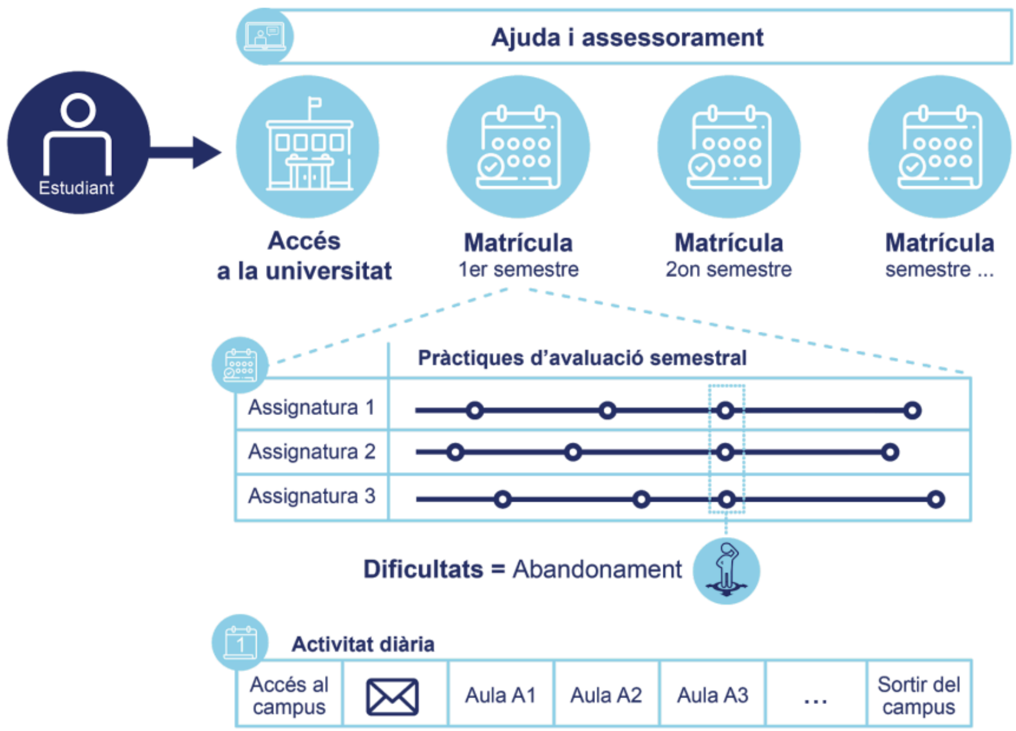
Lee and Choi (2011) investigated online subject dropout factors, identifying three main categories: student factors, subject or program factors, and environmental factors. Student factors, such as academic background and relevant experiences, were found to significantly influence dropout rates. Subject or program factors, including subject design and institutional supports, were also identified as important predictors. Environmental factors, such as work commitments and supportive study environments, were also found to impact students' decisions to drop out. The study highlighted the need for further research in order to understand the interactions among these factors and develop effective strategies to address them. While the current focus is mainly on strategies for subject (course) or program factors, more attention should be given to addressing student and environmental factors. Additionally, the relationship between these factors and enrollment decisions should be explored to gain a more comprehensive understanding of the dropout process. By addressing these issues, institutions can develop more effective strategies to improve student retention and success in online subjects, beginning with the enrollment process.

More recently, and in the context of the UOC, Grau-Valldosera et al. (2019) examined the factors influencing student decisions to take a break and then re-enroll in an online distance learning program. The study identified key differences between continuance intention (the desire to return) and effective re-enrollment, highlighting the importance of both student and environmental factors. The study emphasizes the need for institutions to take preventive actions to improve student satisfaction and support re-enrollment. Specifically, the research found that students' decisions to take a break and re-enroll are influenced by a combination of factors related to the student's individual characteristics, the subject or program and the broader environment. These factors include academic background, relevant experiences, psychological attributes, subject design, institutional supports, work commitments and supportive study environments. Furthermore, the study reveals that while students may have a strong intention to continue their studies, several factors can hinder their ability to effectively re-enroll. These factors include personal circumstances, such as work commitments or family responsibilities, as well as challenges related to the subject or program, such as difficulty or lack of interest in the subjects. Careful consideration of semester workload, including factors such as time commitment and subject difficulty, may be a critical factor in retaining students, mitigating failure and preventing dropout. Therefore, supporting effective enrollment is crucial for making well-informed decisions, as it ensures accurate and comprehensive data is available to guide strategic choices. To foster student retention, it is essential to create a learning environment that supports self-directed learning, accommodates the unique needs of adult students, and empowers them to actively construct their own knowledge. Additionally, students' ability to navigate and utilize information effectively within the online environment is crucial for success. By considering factors such as subject structure, workload and student support, institutions can implement strategies to enhance student engagement and reduce dropout rates (Bawa, 2016).

It is also worth mentioning the ESPRIA project, implemented at the Universitat Oberta de Catalunya (UOC), which aims to enhance student retention and success by providing personalized support and guidance during their first academic course as shown in Figure 2.3 (González et al., 2018). This initiative used institutional learning analytics to create recommendations accordingly, offering flexible learning paths and addressing potential challenges to improve student success and reduce dropout rates in online higher education. Besides, ESPRIA involved collaboration between faculty, advisors and students to create a supportive learning environment. ESPRIA offers students a variety of flexible learning paths, including pre-designed packages of subjects that are tailored to their individual needs and goals. The project utilizes institutional data on student performance, engagement and progress, allowing for targeted interventions and support.

Figure 2.3 - Structure of the ESPRIA project

The ESPRIA project analyzed student activity levels at the UOC (Meneses et al., 2019)*. After completing the enrollment process, students enroll in subjects that require them to submit assignments. Researchers identified common challenges faced by students and developed recommended subject packages suitable for concurrent enrollment during the first semester.*



Continuing this research requires further study to examine student progress beyond the first two semesters (i.e. first academic year). Given the lower dropout rate in these later stages, understanding the specific information needs of students from semester three onwards is essential. In fact, UOC provides two different advisor roles depending on the student semester. One type of advisor for students in their first two semesters and another type of advisor for the rest. Investigating whether data visualization tools could enhance student decision making in their third semester onwards could lead to practical applications and improvements in student support systems.

2.2 Academic advising

The term academic advising commonly refers to interactions involving representatives from higher education institutions, known as advisors, and students, known as advisees. Academic advising can be delivered through various channels, including phone calls, face-to-face meetings, and online platforms such as websites, social media, or email (Chan et al., 2019). Academic advising is part of the learning processes and has a significant impact on educational systems, enhancing student engagement and serving as a method to achieve their success. The advisor role is a multifaceted one. Advisors typically provide guidance and assistance to students concerning personal and professional development, understanding institutional prerequisites, academic studies, selecting suitable subjects (i.e. acting as a human/expert recommendation system), and future aspirations (Chan et al., 2019). They contribute to student development by promoting awareness of learning resources and evaluating student performance (Assiri et al., 2020; Gordon et al., 2008). Many universities around the world have academic advising programs and have extended their academic support services and programmatic interventions (Campbell & Nutt, 2008; Chan et al., 2019). The abovementioned ESPRIA project at UOC can be also considered a good practice in advising (González et al., 2018). If these programs are implemented correctly, they can lead to improved enrollment, subject selection, student satisfaction, outcomes, retention and success (Simpson, 2004; Gordon et al., 2008; Chiteng Kot, 2014; Khalil & Williamson, 2014).

As academic advising usually involves various stakeholders (advisors, students, and institutions), contents and processes; academic advising methods can be categorized into different approaches, including information-based, intervention-based, holistic development, student learning outcomes, and strength and asset building (Y. He & Hutson, 2016). Many institutions combine these approaches and faculty and professional advisors may switch between them based on students' needs. For instance, in the context of the Universitat Oberta de Catalunya (UOC), advisors usually adopt an intervention-based advising approach, identifying potential issues that students might encounter prior to their enrollment or subject selection. Before enrolling, students review the study plan information provided on the university website and other documents. Taking into account their academic record and the potential subjects to be validated, students make an enrollment proposal to the advisor, who assesses whether it is appropriate or not. Therefore, the enrollment process presents a complex challenge, requiring the integration of diverse information sources. These sources range from student-specific data (e.g., academic history, personal goals) to detailed information about subjects (e.g., prerequisites, deadline schedules, difficulty). Surprisingly, in some cases, students do not use this service and others do not take the advisor's recommendations into account (Pitts & Myers, 2023).

Nevertheless, the presence of an academic advising system does not ensure student satisfaction. For instance, in Chan et al. (2019), various projects are analyzed, and it is concluded that in fifteen of the reviewed studies, students expressed positive experiences, while in four of the studies, the experiences were negative. Reasons for student satisfaction include their intention to be advised, the level of trust they have in the advisor, the support provided by the advisor and a higher frequency of interactions, among others. Reasons for student dissatisfaction include the lack of connection between advising and the student's subjects, advisors not meeting students' expectations and communication issues between them. Another interesting highlight from the previous study is the emergence of five projects of online advising systems through websites, social networks, or email. In four of the studies, students mentioned that online communication helped them interact with their advisors, although in one of the studies, students preferred to communicate face-to-face with their advisors. Regarding students' advising needs, many of the reviewed projects suggest that students require support in the enrollment system, information about subjects, assistance in enhancing study skills, aid with academic matters, and guidance in career-related issues (Chan et al., 2019). Moreover, students need additional information about subjects such as the assessment type, the number of assignments, students' opinions about the subjects, etc. (Rivas et al., 2021). However, universities usually provide only a brief subject description and sometimes advisors do not have this additional information to advise their students specifically in this regard (Khalil & Williamson, 2014).

A good online advising process can be time-consuming, so automating some of the advisor's tasks could be used to optimize this process. If web-based tools were introduced into the advising process, advisors could save time on repetitive tasks and dedicate it to assisting students, particularly with their study plans. Furthermore, if there is a crucial moment to receive advice, it is during the enrollment process because, as stated earlier, open and online universities' flexible programs allow students to select subjects in any order. This apparent advantage can be undermined by students and advisors' limited access to the information necessary for making informed enrollment decisions, thus leading to inappropriate subject selections. While advisors can help address this information gap, software is needed to assist them in performing this task efficiently and effectively. For instance, Iatrellis et al. (2017) identified subject recommendation as a key research objective. One of the most common questions is which subjects students should enroll in and in what order they should do so. In fact, effective advising contributes to students making better subject selections (Khalil & Williamson, 2014) and previous research demonstrates that students appreciate advisors who offer prompt responses, possess knowledge about educational programs and assist students in their degree progression (Ortiz-Rodríguez et al., 2005; Irani et al., 2014; Cross, 2018). However, sometimes various stakeholders also refrain from using the provided systems due to an unsatisfactory user experience (Feghali et al., 2011).

Academic advising systems are software applications designed to facilitate the online advising process by automating administrative tasks and enhance communication between students and advisors. These systems typically incorporate features for subject selection, student information management, academic planning, appointment scheduling, communication tools and performance analytics. By centralizing academic data and providing efficient communication channels, these systems aim to enhance student success and advisor productivity. Nevertheless, some advising systems do not consider students' needs or provide inaccurate information about subject prerequisites (Khalil & Williamson, 2014; Meyer & Marx, 2014). In fact, in Sutton and Sankar (2011), it is stated that certain students express their concern regarding information related to subject scheduling and sequencing. Consequently, this led to some students choosing an unsuitable combination of subjects. It is advisable for institutions to provide a variety of internal information sources accessible to both advisors and students (Lowe & Toney, 2000). Therefore, there are many opportunities for improvement to enhance students' experiences with online higher education. Academic advising systems can be developed to improve communication and address other advising needs such as new orientation systems, feedback, and repositories for specific resources (Irani et al., 2014).

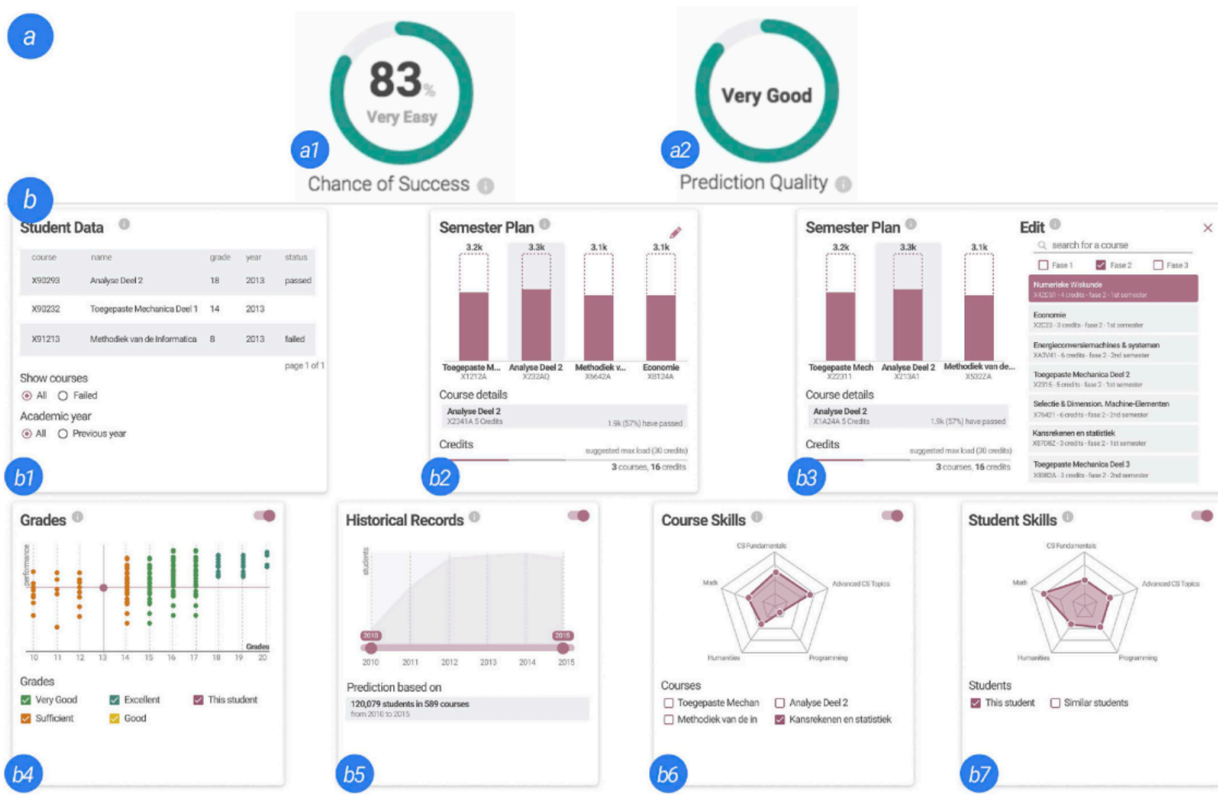
Prior to the development of recommendation systems, which consider both content and user preferences, expert systems were considered as state of the art in providing users with answers within a specific domain. Expert systems reached the peak of their popularity during the 1980s (Gray et al., 2014). Automated advising systems replicate this concept by applying similar principles to academic advising. They try to systematize the knowledge and expertise of human advisors, providing personalized guidance to students. For instance in Golumbic et al. (1986), a knowledge-based expert system for student advising is introduced. The study presents an advising system to assist students in planning their subject scheduling within their academic degree at Bar Ilan University. The study illustrates the viability of utilizing knowledge-based systems in academic planning, leading to modifications in the prototype itself and other concurrent projects emerging from the research. In Wehrs (1992), an expert system is developed to support academic advising at the University of Wisconsin - La Crosse. The system recommends subjects based on those completed by students. The effectiveness of the implemented system is linked to the satisfaction students have with their advisors. The study also unveiled potential user experience changes, such as the enhancement of the processing speed of the consultation. Furthermore, Patankar (1998) presents an expert system solution for academic advising in the Faculty of Aviation at San Jose State University. The system automates some routine tasks of faculty members related to enrollment management. The evaluation of the system revealed the potential for creating a more advanced system, applicable in administrative tasks such as enrollment, placement services, student relations, recruitment, etc. Finally, Lowe and Toney (2000) developed an expert system based on artificial intelligence to replicate the process actually used by experts. Recommendations derived from this research included elevating advising to a higher priority, implementing comprehensive advisor training, clearly defining advising responsibilities, enhancing advising materials, and establishing accountability, evaluation, and reward systems.

Automated or technology-based advising systems can also assist students in better planning their enrolled subjects and avoiding long-term mistakes. For instance, a system can provide information on whether the student has fulfilled the prerequisites to enroll in a more advanced subject the following semester or offer the correct sequence in which subjects should be taken to complete the degree more efficiently. An example of which could be the web-based decision support tool for academic advising by Feghali et al. (2011), which assists students in resolving questions related to their subjects.

A newer literature review presents online academic advising systems that aim to address a range of core advising tasks, with subject selection being the most recurrent one. Nevertheless, other tasks are also important, such as academic program planning, student-advisor communication, academic scheduling, student performance monitoring, retention efforts, providing information, and solving other queries (Assiri et al., 2020). In Ganeshan and Li (2015) a web-based intelligent advising system utilizing collaborative filtering was developed to offer personalized subject recommendations. While promising, limitations included the need for further refinement in recommendation accuracy, especially regarding prerequisites and individual student preferences. Future work involves enhancing the system with advanced clustering techniques, incorporating learning styles and addressing the issue of recommending elective subjects. In Eckroth and Anderson (2019) a subject advising system that uses a planning engine to develop multi-year subject schedules for complex scenarios was developed. By analyzing all possible schedules, it provides insights into optimal subject timing and resource allocation. The authors identified a need to develop more user-friendly interfaces.

Figure 2.4 - LADA learning dashboard

LADA is a learning analytics dashboard designed to support academic advisors in providing personalized guidance to students (Gutiérrez et al., 2020)*. By using various information cards (a to b7), LADA offers insights into student performance and subject history enhancing future planning.*



Another example is LADA, a learning analytics dashboard for academic advising (Gutiérrez et al., 2020), shown in Figure 2.4. The system is designed to enhance advisor decision making. Key functionalities include the overview of chance of success, several information cards, subject selection, filtering and several visualizations such as bar and radar charts to present complex data in an easily understandable format. The learning dashboard successfully represents historical subject records including grades, years taken and pass/fail status. As well as comparing the student's grades to peer averages and allowing for filtering by performance group, enabling users to define the range of student records used for prediction and visualizing the skills required for a set of subjects, comparing them to the student's skills and to the average of peers with similar performance. By comparing LADA to traditional methods, the authors found that it empowers advisors to explore multiple scenarios, leading to better-informed decisions. While LADA is well-received, further research is needed to refine its algorithms and understand its long-term impact on student outcomes.

LADA can be considered a good example of the evolution in the field of academic advising systems. Furthermore, in Guerra et al., (2020) the adaptation and pilot implementation of academic advising dashboards across three Latin American universities is detailed, starting with a an existing advising dashboard (LISSA) from KU Leuven. The resulting distinct implementations were driven by each institution's contextual needs, from establishing new advising processes to enhancing existing ones. The pilot evaluations provided strong evidence of the dashboards' positive impact on advisor satisfaction, usefulness, and supporting decision making. In this regard, two types of systems emerge: the use of traditional recommendation systems and learning dashboards. The subsequent sections will explore the functionalities of each system, examining their respective roles on students, advisors and other stakeholders, and their respective contributions to the advising and other educational processes.

2.3 Recommendation systems

Recommendation systems are software applications that suggest items to users based on their preferences and behavior (Resnick & Varian, 1997; Aggarwal, 2016). These systems utilize algorithms to analyze vast amounts of data, identifying patterns and predicting user interests. By understanding individual preferences, recommendation systems can offer personalized suggestions, enhancing user experience and driving engagement across various topics such as movies, music, books, online education, business, websites, social networks, etc. (D. H. Park et al., 2012; Behera & Nain, 2023). Recommendation systems have become a key feature of digital platforms across different industries like e-commerce, entertainment and social media. The success of recommendation systems is evident in their ability to increase sales, improve content discovery and enhance customer satisfaction (Jannach & Jugovac, 2019). By analyzing user behavior, preferences and historical data, these systems can personalize content, products, and services, enhancing user experience and engagement (D. H. Park et al., 2012). However, these systems also come with risks. They can reinforce echo chambers by promoting content that aligns only with existing beliefs, limiting exposure to diverse perspectives. Additionally, recommendation algorithms may inadvertently perpetuate biases, leading to discriminatory outcomes. Privacy concerns also arise, as vast amounts of personal data are collected and analyzed, sometimes without full transparency or user consent (Furini, 2024). The distribution of research on ethical concerns in recommendation systems reflects the varying disciplinary approaches, with computer science focusing on technical challenges like privacy and fairness, while social sciences address broader societal impacts like manipulability and autonomy (Milano et al., 2020).

The field of recommendation systems is very popular among researchers, with numerous articles available as well as literature reviews (D. H. Park et al., 2012a; Beel et al., 2016; Ko et al., 2022). General recommendation systems are often classified in five different categories, according to their nature: content-based, collaborative filtering-based, knowledge-based, hybrid, and computational intelligence-based (Aggarwal, 2016). Several key approaches can be identified:

- **Content-based filtering:** This approach recognizes that certain items share commonalities, such as belonging to the same category, possessing similar features, or exhibiting related attributes. By analyzing the content of items, the system can generate recommendations for similar items. For example, a music recommendation system might suggest songs by the same artist or within the same genre.
- **Collaborative filtering:** This approach analyzes the preferences and behaviors of users with similar interests or consumption patterns. By identifying patterns within these groups, the system can recommend items that other users with similar preferences have enjoyed. For example, a movie recommendation system might suggest movies that other users who enjoyed the same films as the current user have also rated highly.
- **Knowledge-based filtering:** This approach uses external knowledge sources and expert systems to provide personalized recommendations. By incorporating domain-specific knowledge, such as ontologies, taxonomies, or expert rules, the system can generate more accurate and informative recommendations. For example, a travel recommendation system might utilize a knowledge base of tourist attractions, transportation routes, and cultural information to suggest itineraries tailored to the user's interests and travel preferences.
- **Context-based filtering:** This approach considers contextual factors that may influence user preferences or behavior. For example, a location-based service might recommend nearby restaurants based on the user's current location and time of the day, or an e-commerce platform might suggest products based on the time of year or current trends.
- **Hybrid filtering:** This approach combines two or more of the above techniques to use the strengths of each and mitigate their limitations. For example, a hybrid system might use content-based filtering to generate an initial set of recommendations, and then refine these recommendations using collaborative filtering to consider the preferences of other users. This approach can improve the accuracy and diversity of recommendations by incorporating multiple perspectives and data sources.

In this thesis, we have focused specifically on learning recommendation systems, rather than providing a broad overview of the entire field. The same types of recommendation systems applied to educational contexts can be studied. In practice, most learning recommendation systems exhibit a hybrid nature (Souabi et al., 2021; Raj & Renumol, 2022), integrating aspects from various categories. For instance:

- **Content-based filtering:** Certain subjects can belong to the same learning itinerary, developing similar competencies, or acting as prerequisites for other subjects.
- **Collaborative filtering:** Historical enrollment data and academic performance of students with similar enrollment patterns can be analyzed. The system can recommend subjects that align with the student's academic trajectory.
- **Knowledge-based filtering:** This approach utilizes structured knowledge about the curriculum, such as subject descriptions, learning objectives, prerequisites, and subjects dependencies, to generate recommendations. For example, the system might suggest a sequence of subjects that fulfill degree requirements in the most efficient manner.

- **Context-based filtering:** Contextual factors that may influence subject selection can be considered. For example, the system might account for the fact that some subjects are only offered during specific semesters.
- **Hybrid filtering:** For instance, the system could initially recommend subjects based on their content and prerequisites (content-based and knowledge-based). Then, it could refine these recommendations by analyzing the enrollment patterns and academic performance of students who have previously taken similar subject combinations (collaborative filtering).

Learning recommendation systems have emerged as a significant research area in online and higher education (George & Lal, 2019; Urdaneta-Ponte et al., 2021; Bin et al., 2024), with applications ranging from predicting student performance to informing academic advising. By anticipating student needs and providing personalized guidance, these systems can contribute to improved student retention and success (V. Maphosa & Maphosa, 2023). The abundance of online learning resources presents students with a challenge similar to consumers navigating a marketplace, but not quite the same. Selecting relevant learning materials is crucial for successful learning outcomes. Unlike product recommendations, however, learning recommendations must consider the learner's specific goals, competencies and learning styles (Drachsler et al., 2009). Therefore, general recommendation systems, commonly employed in e-commerce and other fields, cannot be directly applied to online learning without significant adaptations (Zaiane, 2002; George & Lal, 2019). Unlike other popular recommendation systems used in Amazon, Netflix or YouTube, providing students with appropriate subject recommendations needs to take into account not only students' preferences and background but also other constraints related to university policies, such as semestral organization, amongst others. Therefore, contextual information becomes important to provide users with good recommendations (Kulkarni & Rodd, 2020; Behera & Nain, 2023).

General recommendation systems designed for entertainment or e-commerce require significant adaptations before being used in open and online universities (see Table 2 in Buder & Schwind, 2012). As illustrated in Table 2.1, there are fundamental differences between general recommendation systems and learning-specific recommendation systems, such as the items to recommend (subjects instead of songs, products or videos) and the type of user. One of the most important differences is the number of items to choose from. Recommending from a vast repository of millions of songs or products differs significantly from suggesting a limited set of academic subjects. Furthermore, while entertainment platforms often involve single-item selections to be consumed one at a time, students enroll in more than one subject at the same time. For instance, in the case of the UOC, students usually enroll in two or three subjects each semester, while Spotify, Netflix, YouTube or TikTok users can only watch one video at a time. This complexity requires the recommendation system to take into account potential subject combinations and their implications for student workload. Furthermore, in open universities most of the subjects must be enrolled in in order to complete the degree, and it is advisable to do it following a certain order, although not mandatory. Besides, a user can listen to the same song, watch the same video or buy the same product as many times as they want, whereas a subject can only be taken once, unless it is not successfully passed. Finally, it is important to note that the selection of subjects will entail a significant amount of time for the student and that they will be dedicated to them for six months, meaning the concept of consumption is completely different. Furthermore, changing subjects is not possible after enrollment in most cases. Therefore, accurate initial subject choices are important for student success. These key differences show the need for specialized recommendation systems tailored to the unique context of flexible enrollment in open and online universities.

Table 2.1 - Characteristics of recommendation systems

Comparison between classic and learning recommendation systems across several dimensions, including the type of item recommended, the target user, the number of available items, the number of items consumed at once, the necessity of sequential consumption and the user dedication when selecting an item.

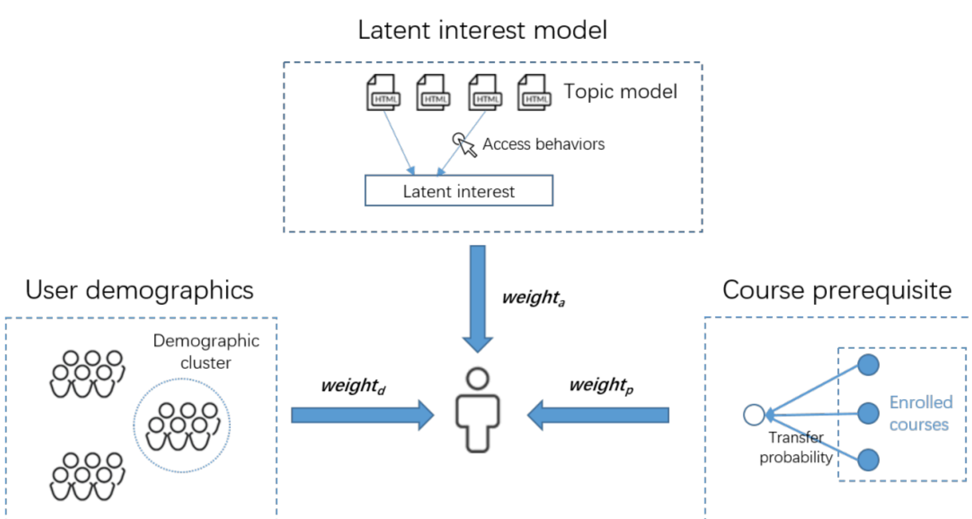
Project / Company	Open Universities	MOOCs	Spotify	Netflix	Amazon	Youtube / TikTok
What is recommended?	Subjects	Courses	Songs	Movies / Series	Products	Vídeos
Who is it recommended to?	Formal education students	Students	Users	Users	Users	Users
Number of items to choose from	Tens	Hundred / Thousands	Millions	Thousands	Millions	Millions
Number of items to choose/consume each time	From 1 to 6	There is no limit	1	1	There is no limit	1
Most items must be recommended (i.e. mandatory)	Yes	No	No	No	No	No
Is it advisable for the user to select the items in a certain order?	Yes	Yes	No	No	No	No
Can you choose the same item more than once?	No, unless it is not passed	Yes	Yes	Yes	Yes	Yes
Dedication time per selected item	Months	Weeks	Minutes	Hours	NA	Minutes

Unlike traditional recommendation systems, which are mostly focused on user preferences, learning recommendation systems must adapt to evolving learner knowledge and activities. Accurately assessing learner knowledge and activities is significantly more complex than determining product preferences due to the extended timeframe and intricate nature of the learning process. In Buder and Schwind (2012) the potential of personalized recommendation systems to enhance learning experiences is investigated. Aligning with key learning science principles, recommendation systems can enhance learner autonomy, use collective intelligence and provide adaptive guidance. However, direct application of traditional recommendation system models to educational contexts is inappropriate due to the unique characteristics of learning environments. The study explains the challenges and opportunities inherent in developing effective learning recommendation systems, considering both learner-centric and system-centric approaches.

It is important to distinguish certain differences between MOOCs and subject recommendation systems in open universities. MOOCs generate large amounts of data that can be used to analyze student behavior, dropout rates, forum participation, video lecture use, procrastination, certification options and cross-course linkages (Diver & Martinez, 2015). Key findings in MOOCs recommendation system research include the negative correlation between procrastination and achievement, the importance of forum participation and video interaction, and the potential impact of certification options on student effort. In addition to the obvious difference between formal and non formal education systems, and the fact that university students (normally) have the ultimate goal of obtaining a degree, there is no recommendation limit for MOOCs, while the number of subjects of a university degree is finite. The time needed to pass subjects or a MOOC course is also an important factor to take into account. For instance, in Jing and Tang (2017), the "Guess You Like" recommendation system is presented. It uses a hybrid content-aware approach to address challenges like sparsity, anti-interest and cold start when recommending MOOCs. By combining user access behaviors, demographics and course prerequisites, the system effectively recommends relevant courses to students (as shown in Figure 2.5). Evaluation results demonstrate significant improvements in recommendation accuracy and user engagement compared to other methods. Although it would be a good example of a hybrid recommendation system applied to education, the system would have to be redesigned if it were to be applied to a subject recommendation system in an open university context. Subjects could only be enrolled in once, an infinite number of them could not be selected per semester and they would have to follow a certain organization within the degree. These additional constraints would require significant changes to the recommendation system.

Figure 2.5 - "Guess You Like" learning dashboard

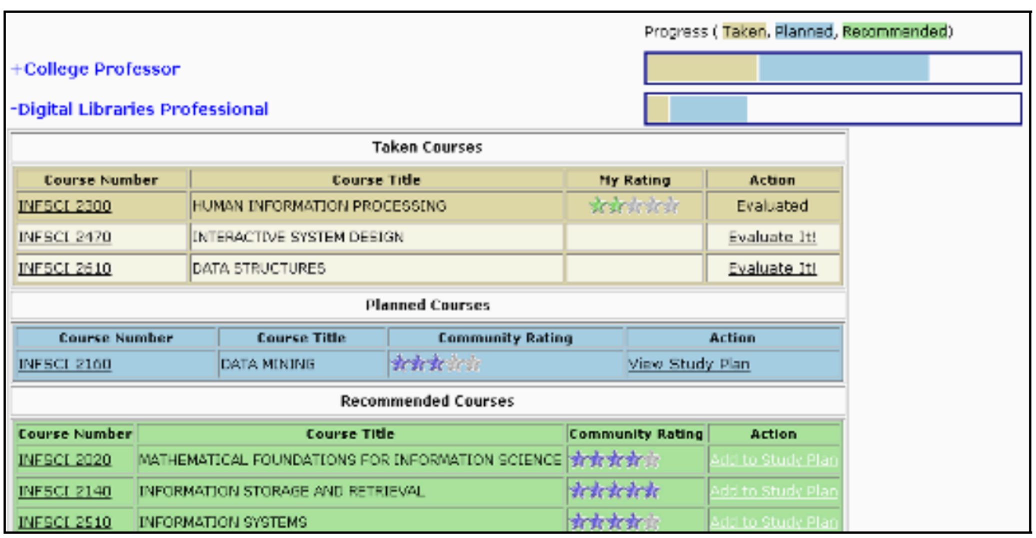
"*Guess You Like" method* (Jing & Tang, 2017)*: a hybrid recommendation system that utilizes user access behaviors, user demographics and subject prerequisites.*



Learning recommendation systems have also emerged as a potential solution to address all the commented challenges using student data and algorithms to provide personalized recommendations for subjects and other learning resources (V. Maphosa & Maphosa, 2023). For instance, in Chen et al. (2005) a personalized e-learning system, PEL-IRT, is proposed. Utilizing Item Response Theory, the system tailors subject materials based on learner abilities and provides adaptive recommendations. Experimental results demonstrate improved learning efficiency and effectiveness. Another example is CourseAgent (Farzan & Brusilovsky, 2006), a community-based advising system that uses student-generated feedback to provide personalized subject recommendations. By combining explicit and implicit user input, the system supports students in making informed subject selections aligned with their career goals by using learning dashboards, although mostly in textual form, such as the one shown in Figure 2.6. In O'Mahony & Smyth (2007) a recommendation system for the University College of Dublin is presented. The research presents a recommendation technology to enhance the on-line module selection process, adding a "more like this" feature. Initial results demonstrate the system's effectiveness, with opportunities for further enhancement through alternative algorithms, refined user modeling and evaluation based on student feedback. In Ray and Sharma (2011), a collaborative filtering approach is proposed to predict student grades and inform elective subject selection. Experimental results demonstrate the effectiveness of this approach in providing accurate grade predictions. Future work will focus on integrating performance prediction with student interest-based recommendation to offer comprehensive academic guidance.

Figure 2.6 - CourseAgent learning dashboard

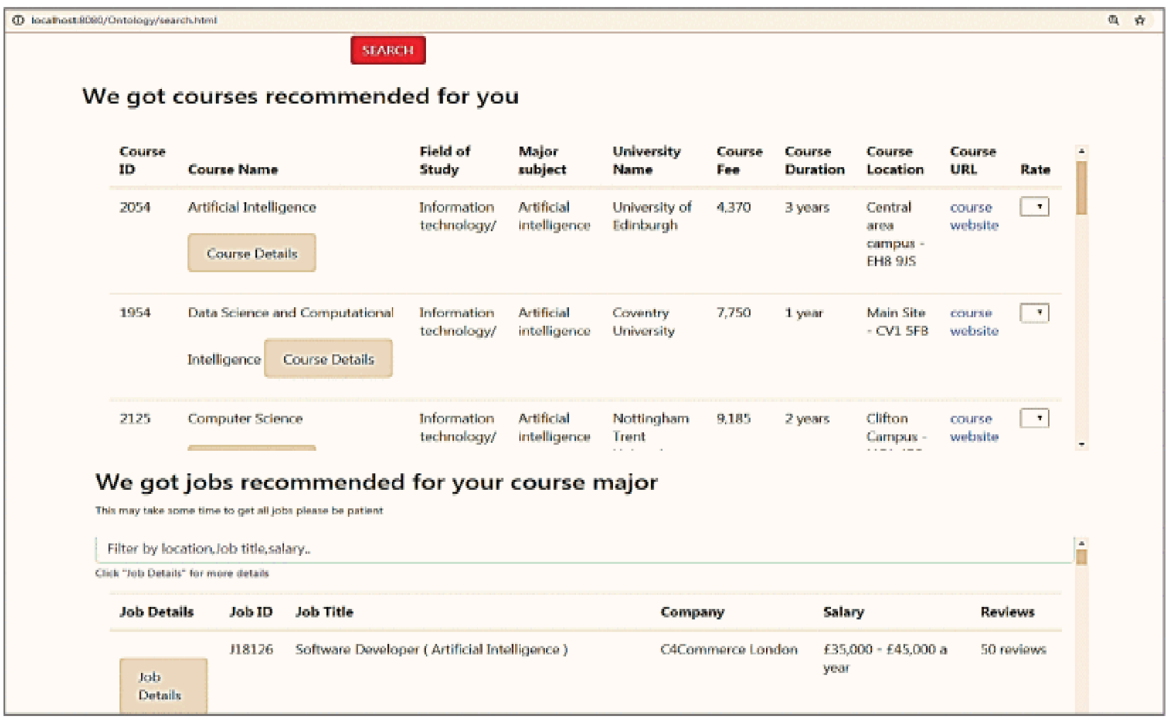
CourseAgent interface (Farzan & Brusilovsky, 2006)*. The upper right section, named Career Scope, displays a progress bar that describes taken and planned subjects towards students' career goals. The system also lists three possible groups of subjects for each career goal: taken (in brown), planned (in blue), and recommended (in green).*



The continued appearance of new research highlights the growing interest in this subject. Lin et al. (2018) proposes a new recommendation system for information management students in Chinese universities. The system uses student enrollment data and an optimization strategy to generate more accurate and efficient subject recommendations. In Gulzar et al.

(2018) a hybrid recommendation system designed to assist students in subject selection is introduced. By using ontology-based knowledge representation, the system provides personalized subject recommendations aligned with individual student needs and goals. Ibrahim et al. (2019) proposes an ontology-based hybrid recommendation system to assist students in selecting suitable university subjects. By combining collaborative and content-based filtering with ontology mapping, the system offers personalized recommendations aligned with student goals and career aspirations, but once again using almost only textual information, as shown in Figure 2.7. Experimental results demonstrate the effectiveness of this approach compared to traditional methods.

Figure 2.7 - Subject and job recommendation learning dashboard
Subject and job recommendation lists interface. Users can search by keywords or by using their user profile (educational background and interests). The system recommends five subjects that users can rate from 1 to 5 (Ibrahim et al., 2019).

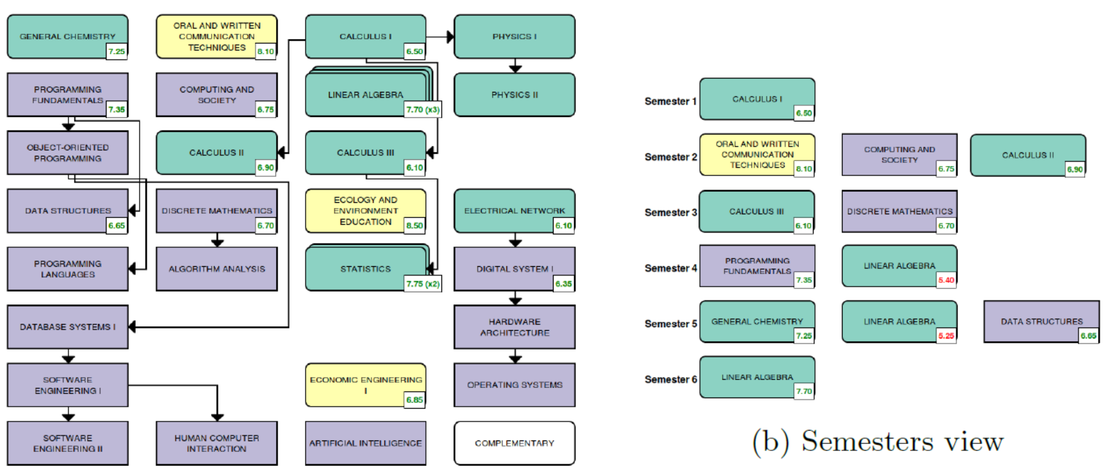


Morsomme and Alferez (2019) introduces a subject recommendation system designed to assist Liberal Arts students at the University College Maastricht in navigating their curriculum. The system utilizes a topic model to identify subjects aligned with student interests and a predictive model to assess subject difficulty and suggest appropriate prerequisites. Evaluation results demonstrate the system's effectiveness in providing relevant recommendations and identifying potential knowledge gaps. However, improvements are needed to ensure coherence between recommended preparatory subjects and the target subject. In Pardos and Jiang (2020) a subject recommendation system for a public university is presented. The study tries to present novel but relevant results for students. The study combines 2 models, one based on subject descriptions and the other on enrollment historical data. Future work will explore strategies to balance novelty and accuracy in recommendation systems. In Esteban et al. (2020) a hybrid recommendation system using collaborative and content-based filtering is proposed to optimize subject selection for students. By considering student preferences, academic performance and subject attributes, the system aims to improve decision making and enhance the overall learning experience.

In Castells et al. (2020) the authors describe a system that takes historical academic data and allows students to select subjects and predict their performance, using classical tables and line charts as a visualization for representing course semestral organization and prerequisites (see Figure 2.8). More recently, in Wagner et al. (2024) a subject recommendation system targeting at-risk students is presented. The system uses student performance data and employs explainable k-nearest neighbor algorithms to offer personalized subject recommendations, demonstrating potential to improve student success and retention rates. Although there are countless examples of subject recommendation systems, previous research demonstrates that there is room for improvement. Challenges such as cold start, data sparsity, and algorithm evaluation remain key areas for future research (Urdaneta-Ponte et al., 2021). While existing research has primarily focused on the development of recommendation algorithms, the design of user interfaces for these systems remains relatively unexplored. Most studies present recommendations in simple list formats, indicating a potential opportunity for innovative interface design.

Figure 2.8 - Program and semesters view

Program view showing the student's career with subjects organized into a grid and linked to their corresponding prerequisites (Castells et al., 2020). Subjects are color-colored depending on their type: basic science (green), humanities (yellow) and professional training (purple).

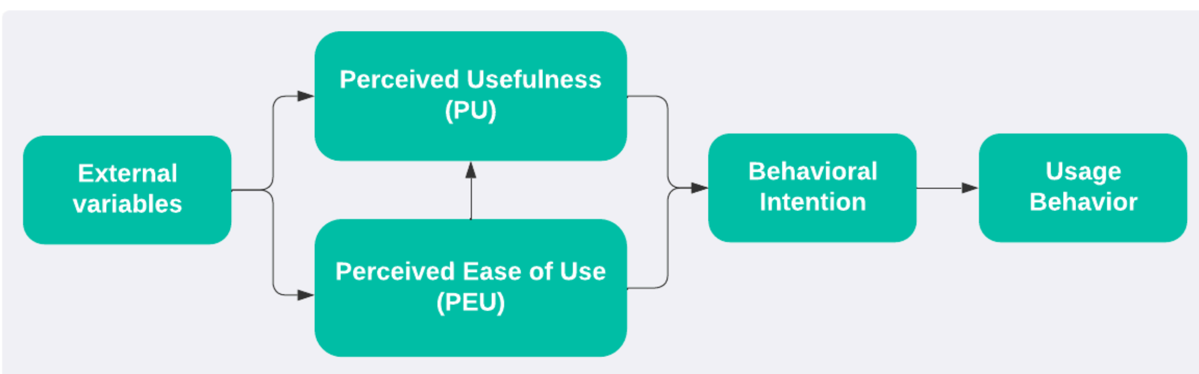


(a) Program view

(b) Semesters view

A specific review of recommendation systems for choosing elective subjects also identified emerging trends that needed further investigation to enhance their effectiveness. Key areas for exploration include the integration of acceptance models to improve recommendation adoption and the analysis of user feedback dynamics (M. Maphosa et al., 2020). The Technology Acceptance Model (TAM) is a widely used framework that explains how users adopt new technologies (Davis, 1989). TAM proposes that perceived usefulness and perceived ease of use are key to technology acceptance (as shown in Figure 2.9). Perceived ease of use refers to the perceived simplicity of using a technology, while perceived usefulness refers to the perceived value or benefits that the technology will provide (Marangunić & Granić, 2015). External variables (such as social influence, organizational support or system quality) can directly influence a user's perception of how useful a technology is and how easy users perceive a technology to be. A technology that is perceived as easy to use is often also perceived as more useful. Conversely, if a technology is perceived as very useful, users might be more willing to invest the effort to learn it, even if it initially seems somewhat difficult. Both perceived usefulness and perceived ease of use directly influence a user's intention to use the technology. Furthermore, if a user intends to use a technology, they are more likely to actually use it. Nevertheless, before applying TAM principles to evaluate a subject recommendation system, it is essential to clearly define the target user population. Understanding the specific characteristics and needs of the intended users and the scenario where the technology will be adopted is crucial to ensure that the TAM model is appropriately applied and evaluated. Moreover, TAM serves as a framework for the development of systems that prioritize user-relevant factors.

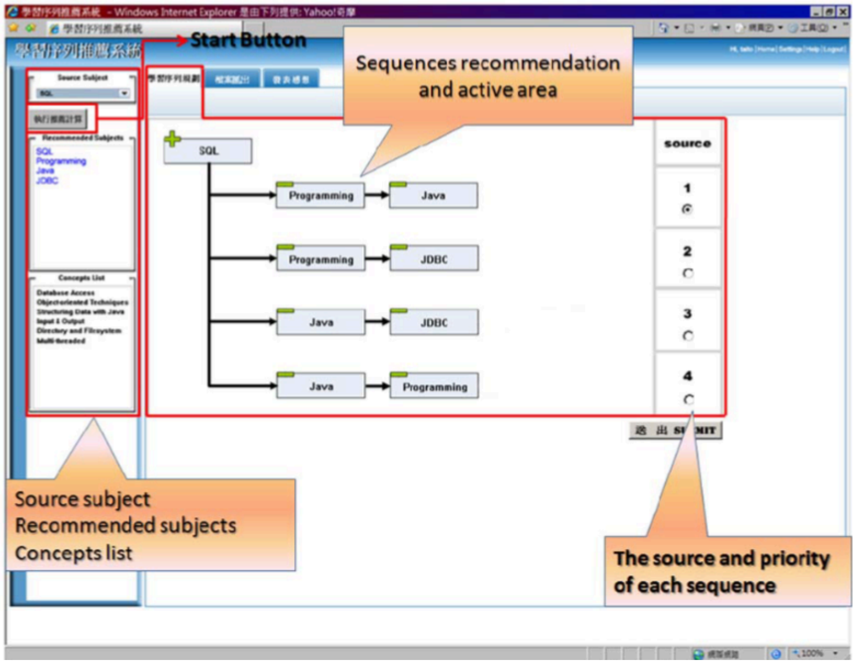
Figure 2.9 - Technology Acceptance Model
TAM (Technology Acceptance Model). Adapted from Davis (1989).



Another of the most common problems found in this field of research is the cold start problem. The cold start problem arises when insufficient data is available to generate accurate recommendations for new users or items (George & Lal, 2019; Panda & Ray, 2022; Bin et al., 2024). In a subject recommendation system, the cold start problem arises when insufficient enrollment data (i.e. academic record) is available for a new student or subject. While the UOC's existing data on subject scheduling and prerequisites mitigates the cold start problem for new subjects, it can be a significant issue for new students with no prior academic records.

Figure 2.10 - Recommendation system integrated in a learning dashboard

Recommendation system integrated in a dashboard (Huang et al., 2009). *Students can see learning sequences after the start button has been pressed. Students can select different subjects according to their own needs or interests.*

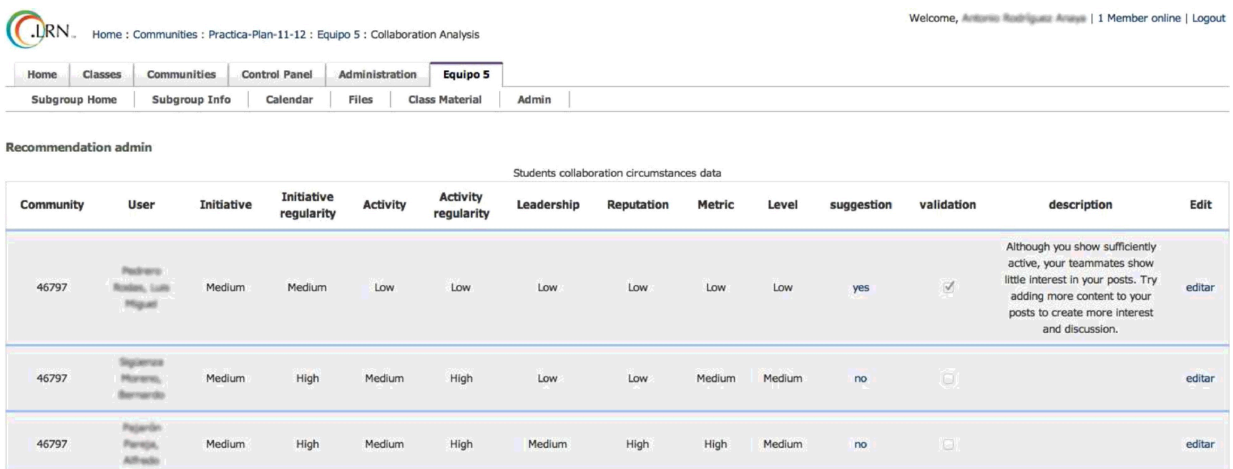


Finally, although recommendation systems and data visualization are emerging fields of study within technology applied to education, there are only a few examples where both are incorporated into a learning dashboard (see Table 8 in Bodily & Verbert, 2017). An example of this approach can be found in Khribi et al. (2008), a study that presents a hybrid recommendation system for personalized e-learning. The system provides real-time recommendations tailored to individual students. Future research will focus on refining the recommendation algorithm and exploring additional personalization strategies. In Huang et al. (2009) a learning recommendation system for e-learning environments is introduced, integrated in a dashboard (see Figure 2.10). The system identifies optimal learning paths that enhance learner efficiency and effectiveness. Evaluation results demonstrate the system's positive impact on learning transfer and student satisfaction. Vesin et al. (2013) presented a personalized e-learning system that uses recommendation and hypermedia techniques to enhance the learning experience. By considering learner preferences, knowledge and peer interactions, the system provides tailored recommendations for online learning activities. The system features distinct user interfaces for students and teachers, with students using the system to access subject content and receive recommendations while teachers manage learner data and provide guidance. Evaluation results demonstrate the system's effectiveness in improving learning outcomes and user satisfaction.

Furthermore, in Santos and Boticario (2013) a methodology for eliciting learning recommendations in online learning environments is presented. By combining user-centered design and data mining techniques, the system generates personalized recommendations that consider learner preferences, context and other factors. The methodology's iterative approach ensures that recommendations remain relevant and aligned with evolving learning needs, allowing active student participation and enhancing the overall learning experience. In Santos et al. (2014) a user-centered approach to developing learning recommendation systems is presented. By incorporating user feedback throughout the design and development process, the proposed system effectively addresses learner needs and enhances the overall learning experience. Finally, in Anaya et al. (2016) a visual decision tree tool used to analyze student collaboration patterns and promote self-reflection is introduced (see Figure 2.11). Evaluation results demonstrate the tool's effectiveness in providing clear insights into collaboration dynamics and facilitating student-driven improvements.

Figure 2.11 - Recommendation system for advisors in a learning dashboard

Recommendation system for advisors integrated in a dashboard. Advisors can review student-specific data and provide personalized explanations to support the decision-making process (Anaya et al., 2016).



In conclusion, we have explored the application of recommendation systems in the context of higher education, specifically within open and online universities. Unlike traditional recommendation systems used in e-commerce or entertainment, learning recommendation systems should be adapted for the unique characteristics of academic environments. These include the limited number of available subjects, the sequential/parallel nature of learning and the need to consider curricular structures and prerequisites. Additionally, learning recommendation systems must adapt to the dynamic nature of student learning, evolving preferences and changing academic goals.

To address these unique challenges, various recommendation techniques, such as content-based filtering, collaborative filtering and hybrid approaches, have been explored. However, the implementation of these techniques in educational settings requires careful consideration of factors such as data sparsity, cold start problems and the evolving nature of student interactions. Moreover, the design of user-friendly interfaces that effectively present recommendations and facilitate user interaction is crucial. Combining recommendation techniques with visualization into interactive recommendation systems can enhance user understanding and control (C. He et al., 2016). A comprehensive analysis of existing systems reveals a focus on transparency and controllability, with visualization techniques playing a key role in supporting user comprehension. By applying this to educational scenarios, future research can contribute to the development of even more effective and user-friendly interactive recommendation systems that could help the learning experience.

2.4 Educational learning dashboards

In general, a dashboard is a visual display of important information needed to evaluate and achieve objectives, which fits on a screen so it can be monitored at a glance. Also called information dashboard, they can provide a visual overview of key information for decision making (Few, 2006). Most dashboards follow the "Visual Information Seeking Mantra" (Shneiderman, 2003) as a guiding principle for designing effective visualizations: *Overview first, zoom and filter, then details-on-demand*. This approach emphasizes the importance of providing a comprehensive overview of the data at a glance, allowing users to zoom in and filter out irrelevant information, and providing detailed information upon request. Shneiderman concludes by noting that while this mantra is a good starting point, it is not exhaustive and further research is needed to explore the full potential of information visualization in different contexts.

The mainstream application of educational technologies has led to the emergence of diverse data sources within educational contexts. These data streams present valuable opportunities for visualization and analysis through learning dashboards, combining the potential of learning analytics with data visualization techniques (Vieira et al., 2018). A learning dashboard is a display that shows different indicators in educational contexts into one or multiple visualizations. While teachers and students are normally the primary target users for learning dashboards, administrators and researchers may also utilize these tools in certain contexts. The specific design and implementation of learning dashboards will vary depending on the unique characteristics of the educational process and underlying technological infrastructure. Most educational learning dashboard research focuses on single-platform data (such as Moodle), nevertheless, a growing trend involves aggregating data from multiple sources, including social media and learning management systems (Schwendimann et al., 2017). Furthermore, the development of effective learning dashboards applied to education needs multidisciplinary abilities such as expertise in educational processes, user needs, data management, design, development, evaluation and so on.

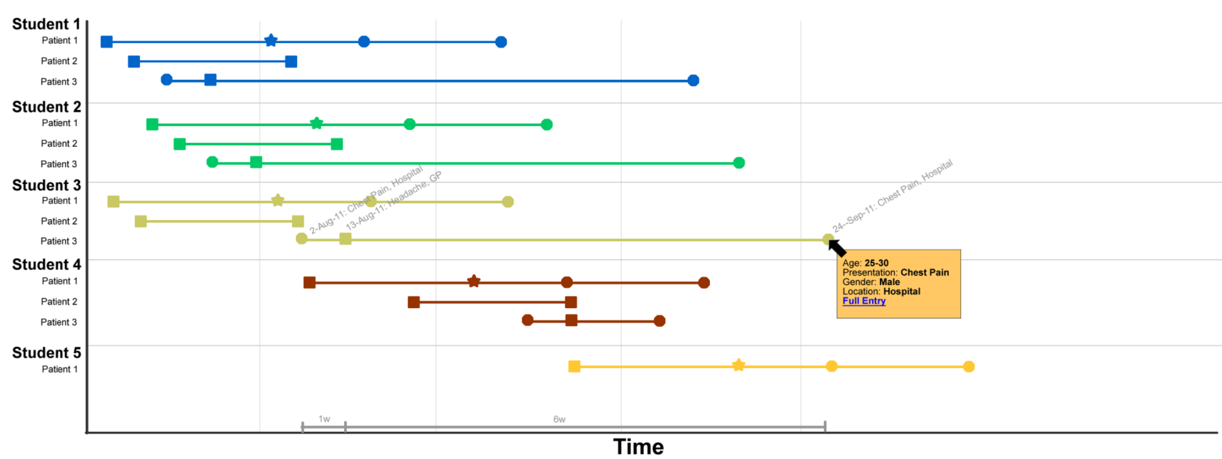
Key challenges in developing effective learning dashboards include identifying relevant indicators for diverse user groups, defining meaningful learning outcomes, creating visualizations tailored to educational contexts and further research in the validation processes (Schwendimann et al., 2017). Bodily and Verbert (2017) highlight key considerations for developing effective educational dashboards, such as: defining system objectives and justify data selection, creating appropriate visualizations, taking into account user needs, creating intuitive designs, reasoning visualization techniques, taking into account student perceptions and behavioral impacts, and explaining how, when, and why these types of systems are used. Designing effective visualizations is crucial for learning analytics dashboards (Bodily & Verbert, 2017). The design of educational learning dashboards usually requires iterative processes that generate different design versions. This approach involves continuous cycles of design, development, testing and refinement, ensuring that the final tool aligns with all users' needs and provides valuable insights. By incorporating user feedback and iteratively improving the design, developers can create dashboards that are both visually appealing and functionally effective, ultimately enhancing the learning experience for students and other stakeholders.

Figure 2.12 - Example of learning dashboard for medical students

First and last learning dashboard for medical students. The design process started with a table and finished with a refined learning dashboard design (Olmos & Corrin, 2012).

					2010-07	2010-08	2010-09	2010-10	2010-11	2010-12	2011-01	2011-02	2011-03	Total
Region 1	**Town 1**	**Placement 1**	**Student 1**	**4044**		1	2							3
				4045		1	1							2
				4047		1	1							2
				4131			2							2
				4224			2	1						3
				4891				1	1					2
				4892					2					2
				4893					2					2
				6141					1		1			2
				TOTAL		3	8	2	6		1			20
			Placement 1 TOTAL			3	8	2	6		1			20
		Town 1 TOTAL				3	8	2	6		1			20
	Region 1 TOTAL					3	8	2	6		1			20
Region 2	**Town 2**	**Placement 2**	**Student 1**	**3716**		2								2
				3720		1		1						2
				3781		3								3
				4185			1	1						2
				4561				1				1		2
				4982					2					2
				TOTAL		6	1	3	2			1		13
			Placement 2 TOTAL			6	1	3	2			1		13
		Town 2 TOTAL				6	1	3	2			1		13
	Town 3	**Placement 3**	**Student 1**	**3867**		2								2
				3868		2								2
				3965		1	1							2
				4053			2							2
				4143			2							2
				5863								2		2
				TOTAL		5	5					2		12
			Placement 3 TOTAL			5	5					2		12

Figure 1: Number of consultations per patient and per month, with group totals

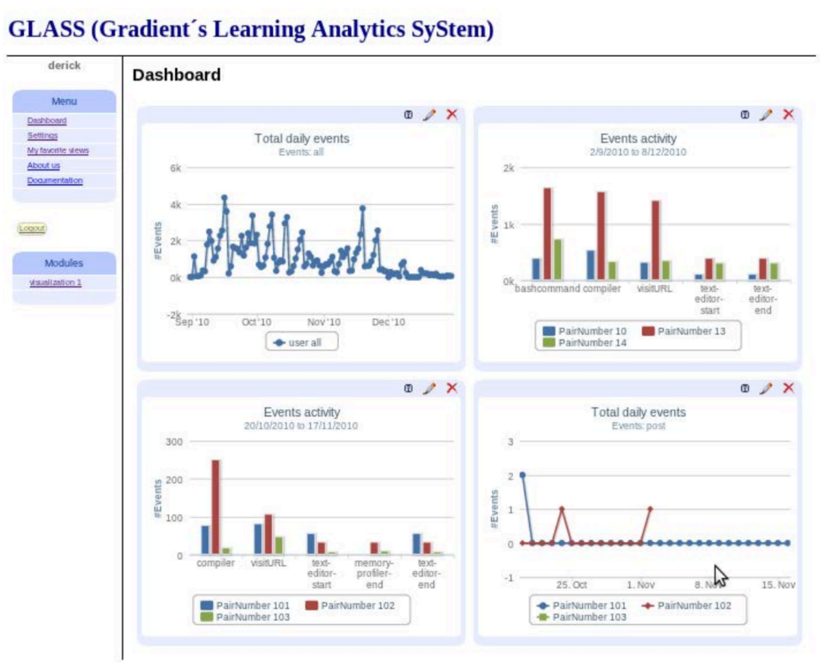


For example, Olmos and Corrin (2012) explain the iterative design process used in developing a learning analytics reporting system, demonstrating the value of continuous refinement and user-centered evaluation. By iteratively exploring different visualization options, the researchers were able to create a more informative and visually appealing dashboard. Following an iterative design process, the initial table format for the dashboard was progressively refined into the final learning dashboard design, as shown in Figure 2.12. The aforementioned LADA learning analytics dashboard was also created following a user-centered design approach (Gutiérrez et al., 2020). UX/UI researchers and academic advisors collaborated on the dashboard design through mind mapping sessions. Feedback from these sessions led to various digital mockups and the final design was evaluated with academic advisors and students.

Visualization types within learning dashboards are broadly represented by a set of few graphical representations. Bar charts, line graphs, tables, and pie charts emerge as the most prevalent visualization types. Notably, these basic visualizations demonstrate certain versatility across diverse educational contexts, serving as tools for conveying information to a broad range of users, from students and teachers to administrators and researchers (Schwendimann et al., 2017). Nevertheless, another challenge might involve avoiding the use of classic static visualizations, which are commonly employed in many learning dashboard projects (Leony et al., 2012; Schwendimann et al., 2017). For example, Figure 2.13 shows GLASS, a web-based platform that facilitates learning analytics by visualizing user interactions and providing valuable insights. Its modular architecture and customizable features allow users to explore data and gain deeper understanding of learning processes. Nevertheless, GLASS utilizes classic visualizations and allows little interaction within its learning dashboard.

Figure 2.13 - GLASS learning dashboard

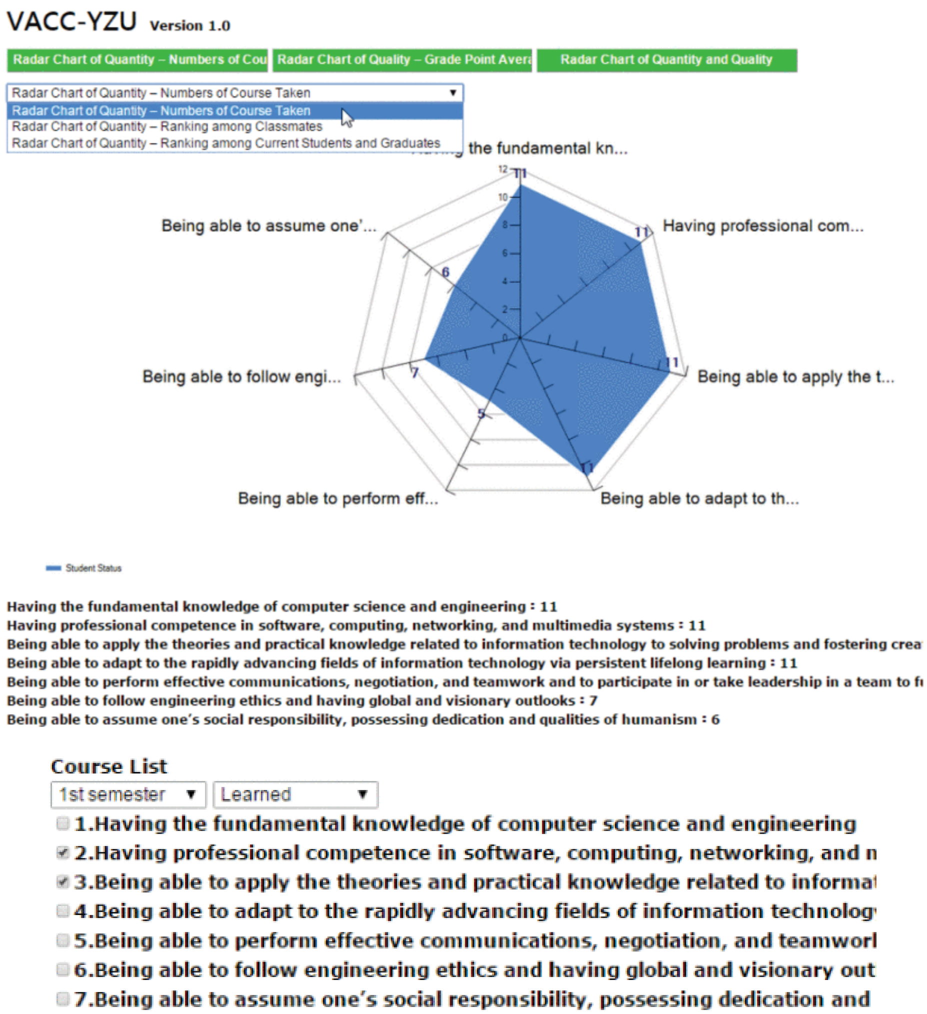
GLASS Dashboard, (Leony et al., 2012).



Even more innovative learning dashboard projects, such as the one depicted in Figure 2.14, often continue to utilize list formats (Chou et al., 2017). This study introduces an approach to develop curriculum-level open student models. By analyzing subject enrollment data and student performance, the system provides valuable insights into student core competencies and facilitates self-reflection. Evaluation results demonstrate the system's effectiveness in supporting student learning and goal setting. Nevertheless, the learning dashboard uses static visualizations that allow little customization and results are shown using a list format.

Figure 2.14 - VACC-YZU learning dashboard

Student Interface of the learning dashboard. The first image shows a student status visualization and the second image shows an inspection tool for assisting students in understanding the correspondence between subjects and competencies (Chou et al., 2017).



Lesson NO.	Lesson Name	Learned	1.Having...	2.Having...	3.Being ...
CS107	Discrete Mathematics...	•	•	•	•
CS380	Web Programming ...	•	•	•	•
CS140	Basic Computer Conce...		•	•	•
CS106	Computer Programming...		•	•	•

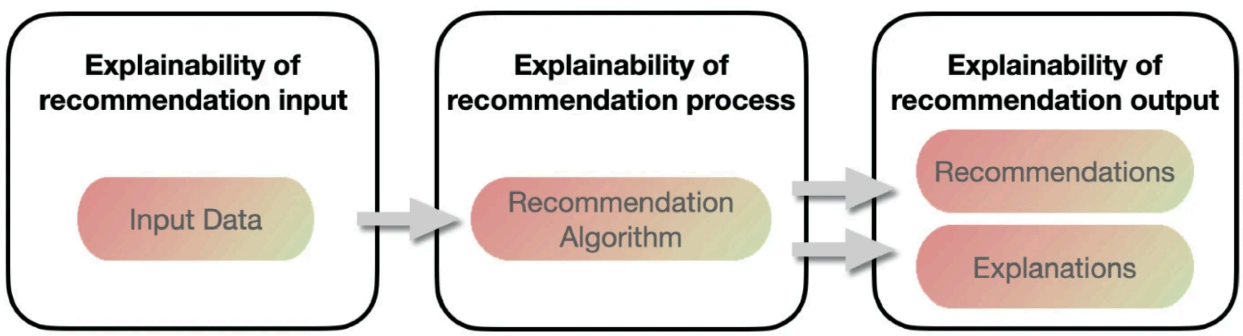
A novel approach is employed by CourseQ, an interactive subject recommendation system developed by Ma et al. (2021). This system utilizes a visual interface for subject exploration, aiming to enhance the transparency and user satisfaction associated with subject recommendations. The dashboard achieves this by providing students and advisors with an overview of their progress, thereby facilitating informed decision making. When selecting a recommended subject, detailed information is displayed on the right sidebar (as shown in Figure 2.15). A grouped bar chart visually represents the topic distribution of the selected subject, aiding comparison with other subjects and informing decision making. The color-coded bars in the chart align with the corresponding circle nodes in the visualization, reinforcing the relationship between the recommended subjects and its thematic content. By analyzing keyword selections and subject interactions, the recommendation system generates recommendations that align with individual student needs. The system allows students to actively shape their recommendations through personalized "like" lists, ensuring customizable results. Regarding its evaluation, while user preferences vary, CourseQ's overall effectiveness in terms of recommendation quality and usability is evident (Ma et al., 2021). Future enhancements could include incorporating additional information and refining the interface for better accessibility. The learning dashboard developed in this research is the closest example that approximates a comprehensive map, guiding students through their academic journey.

Figure 2.15 - CourseQ learning dashboard

CourseQ interface. The upper panel features navigation options such as keyword search, prerequisites, period, time, units, etc. The right panel displays detailed subject information (Ma et al., 2021).

The development of truly interactive visualizations is important in educational contexts to enhance engagement, understanding and effective learning. By considering the diverse needs of students, advisors and other stakeholders, interactive visualizations can go beyond passive data presentation, encouraging active exploration and critical thinking. These visualizations should be designed to be intuitive, visually appealing and responsive to user interactions, allowing students to manipulate data, uncover patterns and enhance decision making. Ultimately, interactive visualizations have the potential to transform the learning experience, making it more engaging, personalized and effective. In a recent paper, Chatti et al. (2024) explores the use of visualization techniques in explainable recommendation systems. It reviews existing research on visual explanations, focusing on their role in enhancing transparency, understanding and user trust. The paper proposes a framework for designing effective visual explanations, considering factors such as explanation aim, scope, method and format. It also discusses the importance of interactive explanations and the potential benefits of combining visualization with other techniques to improve explainability in recommendation systems. Ma et al. (2024) explain that these systems not only provide personalized recommendations but also offer explanations to enhance transparency, user trust and understanding. Figure 2.16 illustrates the explainable recommendation framework. According to the authors, there are two main approaches to explainable recommendation: model-intrinsic and model-agnostic. Model-intrinsic approaches focus on building transparent models, while model-agnostic approaches generate explanations after the recommendation is made. The paper highlights the need for further research in explainable subject recommendation systems to address the gap in educational applications and provide valuable insights for building such systems.

Figure 2.16 - Explainability framework of recommendation systems
Explainable recommendation framework proposed by Ma et al. (2024).



Besides development, the evaluation of educational learning dashboards is a critical research area, essential for understanding their effectiveness in supporting student learning and informing future development efforts. Rigorous validation processes are necessary to assess the impact of learning analytics and dashboards on student outcomes, identify areas for improvement, and ensure that they meet the evolving needs of students and other stakeholders (Bodily & Verbert, 2017; Schwendimann et al., 2017). Gašević et al. (2015) discusses the limitations of current research, such as a focus on predictive models and a lack of integration with educational research. The paper recommends that future research focus on integrating learning analytics with educational theories, considering internal and external conditions, analyzing learning products and strategies, and developing a learning analytics culture that aligns with educational goals. In a literature review, Jivet et al. (2018) examine the evaluation of learning analytics dashboards, which are visual tools designed to empower learners and teachers in online learning environments. The review found that while dashboards are often evaluated for their impact on metacognition and behavior, there is a lack of focus on cognitive, emotional and self-regulation aspects. The evaluation methods primarily rely on self-reported data, tracked data and assessment data. The authors recommend that future evaluations align with the intended learning goals, incorporate a variety of data types and consider the role of learning theories in dashboard design and evaluation. By addressing these recommendations, educators can ensure that learning analytics dashboards effectively support student learning and development. Tretow-Fish and Khalid (2023) highlight another gap in the current research on learning analytics dashboards used in adaptive learning platforms (ALPs). Existing research primarily focuses on design, development and user performance, ignoring deeper pedagogical aspects and teacher points of view. The paper recommends future research to investigate multimodal features, deepen pedagogical evaluation, integrate pedagogical frameworks, include teacher feedback, link data to pedagogy, and focus on cognitive and social impacts to bridge the gap between data analysis and pedagogical practice.

Table 2.2 summarizes the evaluation methodologies employed in studies on educational learning dashboards, based on the review by Schwendimann et al. (2017). It provides insights into the types of participants, evaluation contexts and methods used in the reviewed studies. While most validation studies for educational learning dashboards involve students as primary users, the inclusion of advisors remains relatively scarce, despite the crucial role advisors play in higher education (Klein et al., 2019). This gap highlights the potential for further research exploring how dashboards can be designed and evaluated to meet the specific needs of both students and their advisors. By incorporating advisor feedback in the validation process, researchers can gain valuable insights into the functionalities and data visualizations that would be most beneficial for supporting the advisor's role in student learning and development. The evaluation contexts presented offer insights into the settings where learning dashboards are being studied. The majority of studies were conducted in authentic educational situations (A), reflecting a desire to understand the dashboard's effectiveness in educational contexts. Controlled lab studies (C) were less common, potentially indicating a preference for observations. Regarding evaluation types, surveys (S) and interviews (I) were widely used, suggesting a focus on gathering participant feedback. Qualitative think-aloud studies (Q) were employed to gain insights into user thought processes during dashboard interactions. Field tests (F) and focus groups (G) were used to assess the dashboard's performance and gather collective feedback.

Table 2.2 - Summary of evaluation methodologies
Summary of the evaluation methodologies employed in the selected studies on Schwendimann et al. (2017). The table includes information on type and number of users present in the study, the context and the type of evaluation. Evaluation contexts: A= Authentic educational situations, C= Controlled lab studies, E= Experts, I= Informal, S= Simulations. Evaluation types: S= Survey, I= Interviews, Q= Qualitative think aloud study, F= Field Test, G= Focus Groups.

Paper	Type and number of users			Evaluation context	Evaluation type
	Advisors	Teachers	Students		
Dyckhoff et al. (2012)		4		C	Q-I
Santos et al. (2012)		6 - 5	36 - 10	A	I, F, S
Charleer et al. (2013)			22	A	Sx2
Florian-Gaviria et al. (2013)		20		C	S
Monroy et al. (2013)		210		E	S, G
Rivera-Pelayo et al. (2013)		3	13 - 19 - 50	A	S
Santos et al. (2013)			69	A	S
Bull et al. (2013)			1169	A	S
Aguilar et al. (2014)	9		219	A	Sx2
Charleer et al. (2014)		6		C	S
Corrin and de Barba (2015)			24	A	S, I
Hu et al. (2014)		10	30	A	S
Iandoli et al. (2014)			123	A	F, S
Popescu (2014)			40 - 45	A	S
Park and Jo (2015)			8 - 6 - 73	A	I, F, S
Saul and Wuttke (2014)			80	I	F
Schneider et al. (2014)			4	C	I
Serrano-Laguna et al. (2014)			37	I	Q
Muldner et al. (2015)			209	A	S
Martinez-Maldonado et al. (2015)		4	150	A	I
Martinez-Maldonado, Yacef, et al. (2015)		8 - 1	60 - 143	A, S	Q, F
Tarmazdi et al. (2015)		1	49	A	Q
Vozniuk et al. (2015)		1 - 1	11 - 17	A	I, Q

For instance, Dyckhoff et al. (2012) evaluates the eLAT tool, a learning analytics toolkit designed to help teachers monitor student learning progress. The evaluation found that eLAT is usable, interoperable and extensible. However, it requires improvements in data privacy, real-time operations and indicator design. The authors recommend conducting further field tests to gather more data on the pedagogical usefulness of the tool and to refine the indicator design. Hu et al. (2014) presents an early warning system for identifying at-risk students in online subjects. The system uses data mining techniques to analyze student data and generate rules for predicting student performance. When a student's performance falls below a certain threshold, the system sends alerts to both the student and the instructor. The authors conducted a usability evaluation of the system and found it to be user-friendly and effective in providing timely feedback. In Park and Jo (2015), the LAPA dashboard, a learning analytics tool designed to support student learning, was evaluated in a study. The evaluation involved needs assessment, rapid prototyping, usability testing and pilot implementation. While students found the dashboard easy to use and understand, it did not significantly impact their learning performance. Future research should focus on improving the dashboard's design and functionality to enhance its effectiveness in supporting student learning.

Prior studies have successfully employed the Technology Acceptance Model (TAM) as a framework for evaluating learning dashboards, demonstrating its applicability and effectiveness in understanding user perceptions and adoption (M.-C. Lee, 2010; Rienties et al., 2018; Vasnier et al., 2020). These beliefs influence a person's attitude toward using the technology, which in turn determines their behavioral intentions and actual use. In the context of e-learning, users need to perceive e-learning as useful and easy to use to adopt and continue using it (M.-C. Lee, 2010). For instance, Rienties et al. (2018) explored the use of learning analytics dashboards in teacher professional development. While teachers generally found the dashboards valuable, challenges are interpreting and making sense of the data presented. Vasnier et al. (2020) explored the impact of dashboard design on user perception and adoption. Key factors influencing these perceptions include quantification, visual elements and scaling. Investigating the direct relationship between perceived usefulness, ease of use and intention to use is recommended. When designing surveys, the TAM model can be a valuable framework for gathering user opinions, even if not used to its maximum extent.

Finally, Setlur et al. (2024) argue that dashboards should be designed to facilitate an analytical conversation between the user and the data. The authors propose a set of 39 design heuristics that can be used to create dashboards that are more cooperative and engaging. Nevertheless, after reviewing several learning analytics examples and their validation processes, we have not found any heuristic analysis performed by experts. Fortunately, Nielsen's heuristic evaluation principles might be an interesting approach to evaluate a learning dashboard application (Nielsen, 2024).

2.5 Summary

The review of existing literature reveals a significant gap in research on recommendation systems within the context of higher education. While numerous studies have explored recommendation systems in different industries, research specifically addressing their application to student advising and enrollment processes at open universities remains limited. Furthermore, existing research primarily focuses on textual representations of information (lists or tables), with limited studies exploring the potential of interactive and visual learning dashboards that include personalized recommendations.

This analysis also suggests several key issues for this research. Firstly, the development of effective recommendation systems needs a specific understanding of the specific context and requirements of the educational environment. Open universities, with their unique characteristics and challenges, present an opportunity for exploring innovative approaches to student support. The enrollment phase represents a critical learning process where personalized guidance and support are particularly valuable. Secondly, the integration of a recommendation system within a visual learning dashboard offers a chance for enhancing student engagement and facilitating informed decision making. Finally, a rigorous evaluation of the learning dashboard's effectiveness is crucial, as there is limited existing research on the impact of learning analytics dashboards on student outcomes. This evaluation will identify areas for improvement, ensuring its alignment with student and advisor’s needs and the proper inclusion of the dashboard in the enrollment educational process.

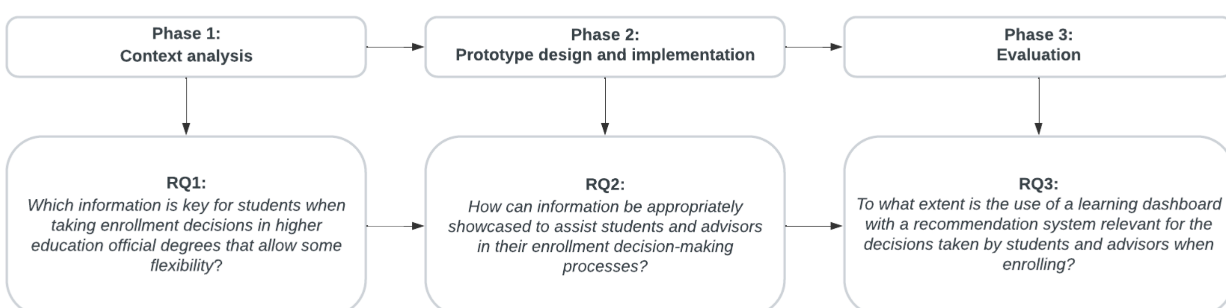
In summary, the limited existing research on visual recommendation systems in open online higher education highlights a significant gap in the field. Consequently, this thesis aims to address this gap by investigating how visual recommendation systems integrated in learning dashboards can enhance the educational experience for learners in open online higher education. By combining data-driven recommendations with intuitive visual interfaces, this thesis seeks to offer new insights into how visual cues and personalized suggestions can help learners navigate vast educational content more effectively, making informed decisions that are tailored to their learning needs and preferences.

Chapter 3
Research methodology

This thesis investigates the potential of a prototype to enhance decision making within the enrollment process at open and online universities. Specifically, this study focuses on the Computer Science degree offered by the Universitat Oberta de Catalunya (UOC) as a case study. The methodology used in this process was inspired by that of Oates et al. (2006) and has three phases: Context analysis, prototype design and implementation, and evaluation. These three phases are related to the three research questions presented in Chapter 01, as shown in Figure 3.1. In summary:

- **Context analysis:** An analysis of the current enrollment process at the UOC was conducted, identifying key challenges and opportunities for improvement. The data gathering methods used were mainly web metrics and a questionnaire.
- **Prototype design and implementation:** Based on the context analysis, a prototype was designed and developed to facilitate improved communication and decision making between students and advisors, by using a design and creation research strategy. This strategy involved several tasks such as the creation of design proposals for the recommendation system, as well as an initial proof of concept, followed by a prototype and several improvements to this prototype. The data gathering methods used were simulations and interviews.
- **Evaluation:** An evaluation was conducted to assess the effectiveness and usability of the developed prototype. The data gathering methods used were interviews, questionnaires and a heuristic study with experts.

Figure 3.1 - Diagram of project phases
Project phases of this study.



At the end of this chapter, we address the limitations and ethical considerations derived from this study; providing a description of the data collection procedures, institutional approvals, and the steps taken to minimize any potential impact on real-world student enrollment decisions.

3.1 Research process

The experiences and motivations along with the research questions have already been revealed in the introduction of this thesis and, in Chapter 2, we have presented "State of the art". In this section, we present the research strategies, data collection methods, and analysis techniques that are employed to address the research questions and contribute to the existing field of study. Furthermore, all strategies and data generation methods have been ordered in different tasks within a proper research process employing the three-phase approach shown in Figure 3.2. In order to perform all phases, we employed a multifaceted approach involving the analysis of web metrics, questionnaires, simulations, interviews with both students and advisors and a heuristic evaluation with experts, as described in Table 3.1. It is important to note that this whole process was focused on the distinct needs and perspectives of both students and academic advisors. User Experience design was used during prototype development to enhance its usability, accessibility and overall user satisfaction.

Figure 3.2 - Extended diagram of project phases

Research process adapted from the model of the research process proposed by Oates (2006). The graph presents phases, strategies, data gathering methods, tasks and their correlations.

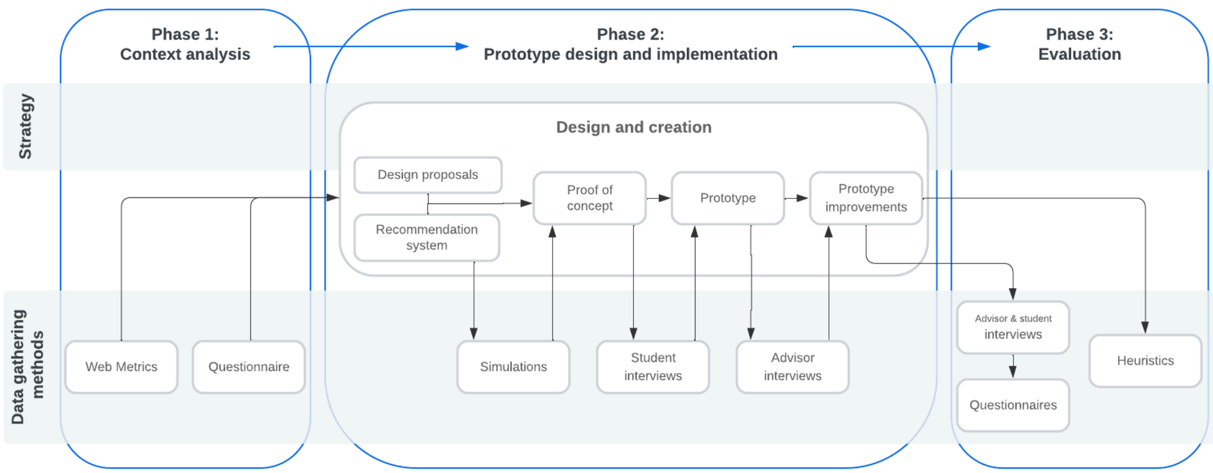


Table 3.1 - Data generation methods

Data generation methods used in all phases, along with the utilized tools and analysis techniques.

Data generation methods	Tool	Analysis approach
Web metrics	Universal Analytics	Quantitative
Questionnaires	Qualtrics and Google Forms	Quantitative and qualitative
Simulations	R scripts	Quantitative
Student and advisor interviews	Google Meets	Qualitative
Heuristics	Google Docs	Qualitative

To establish a solid foundation for the design and creation strategy, we first analyzed the context: the current enrollment process at the UOC and the students' sources of information.

This analysis was key to answering RQ1: *Which information is key for students when taking enrollment decisions in higher education official degrees that allow some flexibility?* This initial phase employed a context analysis approach, focusing on understanding the existing enrollment process and its information sources. The context analysis involved several methods that aimed to identify key challenges and opportunities for improvement in the enrollment process, ultimately informing the design of the subsequent prototype. The data gathered during this phase provided essential insights for the whole project, as detailed further in Chapter 4.

Firstly, we conducted a comprehensive analysis of the university's existing website, which serves as the primary information source for prospective and current Computer Science students. We aimed to identify potential areas for improvement and gather insights that could inform the design of the prototype. Web Analysis was used to investigate the performance and effectiveness of Computer Science Degree program pages from UOC's website (*Grado Online En Ingeniería Informática | UOC*, n.d.) as shown in Table 3.1. Universal Analytics was employed, as it was the analytics tool at the time of the study. Universal Analytics was a version of Google Analytics that allowed us to track user behavior across multiple devices and platforms. It provides a view of user interactions within the website, enabling it to measure key metrics such as user acquisition and behavior. Note that this version of Google Analytics is no longer available. By collecting and analyzing data on website traffic, web metrics provide us with valuable insights for understanding user experience. These metrics included indicators such as unique visitors, page views, time on site and bounce rate. Nevertheless, while this quantitative data analysis provides valuable insights into user behavior, it may not fully capture the reasons behind user decision making (Kaushik, 2009). Therefore, qualitative data, gathered by means of a questionnaire with open responses (further discussion to follow), complemented our initial quantitative analysis by providing rich contextual information and uncovering underlying motivations. The results of this analysis can be found in Chapter 4, section 4.2.

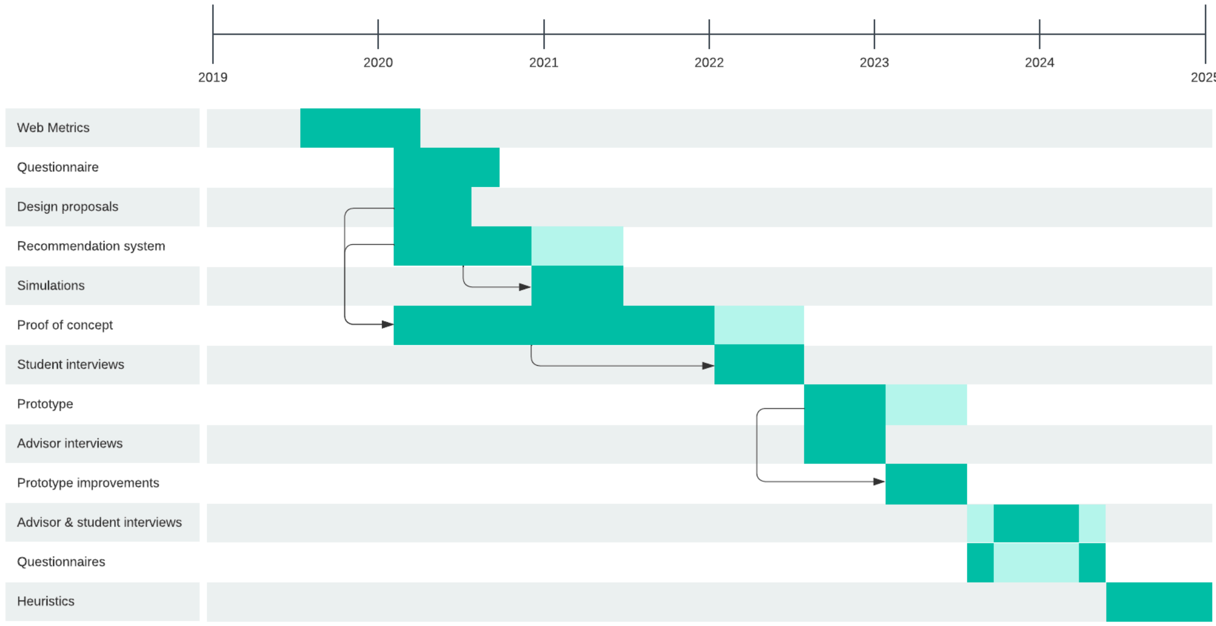
Secondly, we performed a two-iteration questionnaire with students to gain a deeper understanding of their information needs, preferences and perceptions of the enrollment process. Questionnaires were used to understand student preferences for information about the Computer Science degree, in particular how such information could support their subject selection decisions and where they found it. Our objective was to develop a comprehensive list of the factors that influence student enrollment decisions. This involved identifying the most relevant descriptive topics, understanding the role of information sources, analyzing the factors that determine subject selection, and exploring students' motivations and overall perceptions of the enrollment process. This questionnaire was administered via Qualtrics, as it was the official tool at UOC at the time of the study. The results of this analysis can be found in Chapter 4, section 4.3.

The second phase, prototype design and implementation was adapted from the Design and Creation strategy (Oates et al., 2006), centered on the development of a novel IT *artifact*, referred to as *prototype* in this thesis. This prototype was a learning dashboard that included a recommendation system to address the informational needs of open and online higher education students and advisors, specifically in the Computer Science degree at UOC. This second phase provided insights for answering RQ2: *How can information be appropriately showcased to assist students and advisors in their enrollment decision-making processes?* The design and creation strategy comprised five distinct tasks, each informed by specific data gathering methods, as can be seen in Figure 3.2.

Initially, design proposals were generated concurrently with the development of a recommendation system taking into account the data generated in the first phase. Once the recommendation system was created, we conducted simulations using R scripts that produced quantitative data and insights. Simulations were used to mimic the enrollment process. By simulating enrollment decisions based on different factors and comparing the simulations to actual student enrollment data and subsequent grades, we identified some enrollment trends. These trends were used to improve the prototype and consequently these insights, coupled with the selected design proposal, were integrated into a proof-of-concept. Through interviews with advisors and students, we were able to gather qualitative data on the prototype's usability and effectiveness. This feedback approach enabled us to identify areas for improvement such as; refining the user interface, enhancing the recommendation system, improving visualizations and optimizing the overall user experience. After this iterative process of design, testing and refinement, we created a final version of the prototype for validation. An external developer was then hired to complete the prototype and a master's degree student (as part of his master's capstone project) helped us to install it in an UOC's server in order to use it for the final validation.

Finally, to evaluate the prototype a mixed-methods approach was employed, incorporating surveys, interviews, and a heuristic evaluation to answer *RQ3: To what extent is the use of a learning dashboard with a recommendation system relevant for the decisions taken by students and advisors when enrolling?* As stated in Chapter 2, key challenges in developing learning dashboards include identifying relevant indicators for diverse user groups, defining meaningful learning outcomes and creating appropriate visualizations. Additionally, further research is needed to validate the effectiveness of these dashboards (Bodily & Verbert, 2017; Schwendimann et al., 2017). Therefore, a critical aspect of this research process was the validation of the prototype. To achieve this, we conducted a series of simulated enrollment scenarios involving students and advisors. We utilized interviews and questionnaires to gather qualitative data conducted via Google Meets and Forms, as they are widely accessible and easy-to-use tools within the UOC's technological infrastructure. Furthermore, these interactions allowed us to assess the prototype's effectiveness in a real-world context and identify key areas for improvement. At the same time, several conclusions were drawn regarding the impact of the prototype on the enrollment process. To complement this, we conducted a heuristic analysis with two experts, documentation and analysis rubrics facilitated by Google Docs. This further allowed us to assess the usability and user experience of the prototype; identifying strengths, weaknesses and areas for improvement. The complete project timeline is illustrated in Figure 3.3.

Figure 3.3 - Project timeline
Timeline of the different research process tasks.



3.2 Population

The population of this study involved a diverse range of participants, including users of the UOC Computer Science website (for the first phase), and current Computer Science students and their academic advisors (for all the phases). Initially, our research focused solely on the perspective of students. However, upon analyzing the initial questionnaire data, it became evident that the role of advisors in the enrollment process was rather significant. As a result, advisors were included as key participants in the study, providing a more comprehensive understanding of the enrollment process.

The sample of participants in the different data generation methods were rather diverse, depending on each method. For instance, **web analysis** investigated Computer Science Degree program pages from UOC's website users. These users included not only students and advisors, but also other institutional staff or even users interested in completing the Computer Science Degree at the UOC. The analysis of website metrics made it possible for us to know the sections in which users were most interested. While quantitative data from the website provided some insights, it was insufficient to fully understand students' motivations and enrollment preferences. Student feedback was required. Therefore, **a first questionnaire with two iterations** was sent to Computer Science students. Further details are provided in Chapter 4, Section 3. The first iteration of the questionnaire, employing a convenience sampling method served to conduct a preliminary factor analysis. The results of this analysis were then utilized to refine and improve the questionnaire for the second iteration, which was administered to all students enrolled in the degree program. The insights derived from these initial sources of information were subsequently employed in the creation of the proof of concept.

In order to finalize the prototype's development, user feedback sessions with real students, simulations, and advisor interviews were conducted to evaluate and refine the proof of concept. Regarding the **first round of student interviews,** this was conducted with four students that had indicated that they wanted to participate in future studies in the first questionnaire. The data gathered from the two iterations of the questionnaire was essential in addressing RQ1 and informed the second phase of this research. **Simulations** gathered data from students up to the current semester at the time (2020/2). The purpose of this test was to investigate potential underlying patterns in student enrollment choices that were not apparent in the data gathered from the first questionnaire. Later, a **first round of advisor interviews** was conducted with advisors that had volunteered for the study. Advisors were contacted through the Director of the Computer Science Degree. The data gathered from these studies was used to determine the final prototype's design.

Furthermore, for the final validation procedure, we performed **student and advisor interviews and questionnaires** with advisors and students; all of whom volunteered. These interviews facilitated the improvement and later validation of the prototype and provided essential data for responding to RQ3. To conclude, a final **heuristic evaluation** was performed by two experts. These consultations were performed to ensure a comprehensive understanding of the system's strengths and weaknesses. They aimed to both validate the user-derived data and inform recommendations for future implementations.

3.3 Limitations

While both quantitative and qualitative research offer valuable insights, it is crucial to acknowledge the inherent limitations of each approach. On the one hand, quantitative research may oversimplify complex phenomena by reducing them to numerical data, potentially losing important nuances and contextual information (Queirós et al., 2017; Castillo Iglesias, 2019). While correlations can be identified, establishing causality can be challenging, as observed relationships may be influenced by other factors (Castillo Iglesias, 2019). On the other hand, qualitative research findings are difficult to generalize to wider populations because they are not statistically tested. The results may be specific to the studied group and may not apply to a broader audience, focusing on specific cases or small groups, making it difficult to generalize findings to larger populations. Moreover, the researcher plays a significant role in qualitative research, collecting and interpreting data. The researcher's interpretations and biases can significantly influence data collection and analysis, potentially leading to biased or skewed results (Ochieng, 2009; Queirós et al., 2017; Castillo Iglesias, 2019).

Additionally, while both quantitative and qualitative research methodologies possess inherent limitations, the practical application of this research also presents unique challenges derived from its specific context. This study's scope is inherently limited to the UOC Computer Science degree. While the prototype was designed with potential adaptability to other UOC programs, its implementation in other universities would likely face significant technical and organizational challenges. Differences in data collection methods and data availability could prevent its direct application. However, the core functionalities of the prototype, such as the recommendation system and visualizations, could be valuable for other open and online universities and the design and main UX features could be tailored to their own systems. For instance, in the case of traditional institutions, with less enrollment flexibility, the recommendation system could still be applied for elective subject selection.

Finally, limitations in the data gathering methods should also be considered when interpreting the results and generalizing the findings of the study. **Web Analysis** lacks information on the specific identity and motivations of website users. They could be students, advisors, institutional staff, general users interested in the Computer Science degree, etc. Besides, it does not provide information about the motivations behind consulting the analyzed pages. In regard to the **first questionnaire**, it relied on voluntary participation, potentially leading to a biased sample that may not accurately represent the entire population of students. Additionally, the accuracy of self-reported data can be influenced by various factors, such as recall bias and social desirability bias. As for the **first round of student interviews,** the small sample size (four students) may not have captured the full range of student experiences and perspectives, although the conclusions of these interviews helped us with the design and UX. Concerning **simulations**, passing or failing a subject depends on several factors, some of which are related to students' personal characteristics, including their context (job and family commitments) during that semester. Nevertheless, simulations capture the collective intelligence and behavior of students. In relation to the **first round of advisor interviews,** voluntary participation may limit the diversity of advisor perspectives. As for the final validation procedure (**student and advisor interviews and questionnaires**), the actual number of participants (27 students) was lower than the initial target (36), potentially impacting the generalizability of the findings. Regarding the **heuristic evaluation**, it was initially sent to four experts, but only two responded due to lack of time. The participation of only two experts may have limited the range of perspectives and insights obtained during this evaluation.

While the development and evaluation of the prototype were constrained by all of these limitations, we aimed to collect both quantitative and qualitative data to address the core research questions. Ideally, a large-scale, quantitative study would have been conducted to assess the impact of the prototype on a wider population of students and advisors. However, due to technical constraints and resource limitations, we were unable to test the prototype with a broader user base. One of these limitations was to connect the prototype with the institutional login system. The other was to fine-tune the recommendation system and its technical aspects. In fact, this may even require a second thesis performed by a student specialized in recommendation systems development.

Despite these challenges, the data collected through various methods including questionnaires, interviews and simulations, provided a solid foundation for understanding the potential benefits and limitations of learning dashboards and recommendation systems in the context of higher education enrollment. Ultimately, the goal of this research was not to solve the problems within the UOC enrollment system, but to answer fundamental questions about student enrollment decision making and the role of technology in supporting this process. Specifically, our research aimed to identify the key information needs of students, explore effective ways to visualize and present information, and assess the impact of personalized visualization and recommendations on enrollment outcomes.

3.4 Ethics

This research has taken into account the ethical principles according to the UNESCO Universal Declaration of Bioethics and Human Rights (UNESCO, 2005), the Declaration of Helsinki (WMA, 2024), and the Belmont Report (U.S. Department of Health and Human Services, 2018). Concretely, our methodology emphasized the principles of beneficence, non-maleficence, autonomy and justice, ensuring the protection of human rights, the dignity of human beings, and the right to privacy and data confidentiality. This commitment to ethical conduct guided the selection and implementation of all research methods. Furthermore, the European Union has established a legal framework to protect individuals' privacy and data rights. Key legislation includes the General Data Protection Regulation (GDPR), the Law Enforcement Directive (LED), and the Data Protection Regulation for EU Institutions (*Legal Framework of EU Data Protection - European Commission*, n.d.). The applicable regulations are among the most stringent globally and are subject to frequent updates. Any project that involves web analysis must provide transparent information to users regarding: the type of data collected, the individuals authorized to access the data, the data storage methods, the intended purposes of data collection, and the individuals responsible for data management, among other requirements. To ensure strict adherence to EU data protection regulations, the Universitat Oberta de Catalunya encourages PhD students to develop a comprehensive data protection protocol for the thesis and every data generation method that involves the direct participation of students. The following protocols were created, sent and approved by the UOC's Ethics Committee:

- PhD thesis, TFM and TFG research protocol form, submitted in 2020
- First questionnaire:
    - Protocol for the first iteration
    - Protocol for the second iteration
- Final evaluation process: Ethical and data protection protocol form in Doctoral Thesis projects, submitted in 2023

Regarding the first questionnaire, the implementation process was relatively straightforward, as the institution's existing Qualtrics platform was used for both iterations. To ensure compliance with data protection regulations, informed consent was obtained from participants, who were required to explicitly agree to the terms and conditions outlined at the beginning of the questionnaire and in a dedicated landing page. The questionnaire itself included a section where participants could indicate their willingness to be contacted for future research purposes. As aforementioned, this allowed us to identify potential candidates for the follow-up informal interviews with students.

Implementing the data collection procedures for advisor interviews and the final evaluation proved to be more complex. It required careful coordination with the degree director to obtain necessary approvals and ensure compliance with institutional guidelines. To inform potential participants, an informational message was posted on the notice board, specifying the study's objectives, procedures and ethical considerations. Participants were required to provide explicit consent by signing a consent form. Additionally, detailed information was provided to both students and advisors prior to interviews and questionnaires to clarify the purpose of the study and their role in the process. Crucially, the evaluation of the prototype did not interfere with the current student enrollment process. Testing was conducted post-enrollment, ensuring that the prototype's functionality did not influence student choices during the initial registration period. This approach minimized the potential for unintended consequences and ensured that student enrollment decisions remained independent of the prototype's recommendations.

To ensure ethical compliance, the research strictly applied the guidelines provided by the ethics committee. These guidelines implied the following:

- **Data anonymization and storage:** Interview recordings were transcribed and deleted after the study. Participant identities were anonymized using unique identifiers (hash). Only files containing anonymized data were saved.
- **Data usage:** Data was used exclusively for the purposes outlined in the research proposal. Any future use of the data would require explicit justification and, if necessary, additional consent from participants.
- **Data retention:** Personal data was retained only for the duration of the research project. Once the thesis had been completed and defended, all personal data was securely deleted. Non-personal data, such as anonymized transcripts and statistical analyses, could have been saved for potential future research.
- **Data security:** Appropriate security measures were implemented to protect the confidentiality and integrity of the data, including secure storage within the UOC's systems, access controls and user data anonymization.

These guidelines were strictly adhered to throughout the research process to ensure the ethical handling of participant data.

3.5 Summary

This thesis employed a mixed-methods approach, combining quantitative and qualitative data collection techniques, to investigate the potential of a prototype to enhance decision making within the enrollment process at open and online universities. The research followed an iterative design and development approach, incorporating user feedback within each task to refine the prototype and ensure its usability. The project's three phases are structured to address the three research questions (RQ).

The study began with a thorough context analysis, examining the current enrollment process at the UOC and identifying key challenges and opportunities for improvement. This analysis, which included web analytics and a two-iteration questionnaire, provided crucial insights into student information needs and preferences. Based on the findings of the context analysis, a learning dashboard incorporating a recommendation system was designed and developed. This phase involved iterative design, prototyping and simulation, culminating in the creation of a functional prototype. Finally, an evaluation process was conducted employing surveys, interviews, and a heuristic evaluation to assess the prototype's effectiveness and its usability. This evaluation provided valuable insights into the impact of the learning dashboard on student and advisor behavior.

During all of the research phases, this thesis has followed all of the research and ethics recommendations stated by UOC, including them in the research methodology and integrating the specific ethical guidelines for data collection and participant rights.

Chapters 4, 5 and 6 present the outcomes of each project phase, derived through the application of the described methodology.

Chapter 4
Student information needs

This chapter explores the UOC enrollment process. The different phases, information sources utilized by students and the unique aspects specific to UOC are examined. Additionally, the findings from two related investigations are reviewed. These investigations include a web analysis and two-part student questionnaire. Finally, this section concludes by summarizing the research findings and addressing the first research question of this thesis: Which information is key for students when taking enrollment decisions in higher education official degrees that allow some flexibility?

4.1 UOC enrollment process

Initiating Computer Science studies at the UOC requires navigating a unique online enrollment process. From the moment the decision to enroll is made, until the process is completed, a series of steps must be followed in which certain information is sent and received (Table 4.1). The responsibility for making a good enrollment decision is placed on the student, although several tools are made available to them by both the institution (in this case the UOC) and their advisors, with which they can interact.

Table 4.1 - Current enrollment process steps
Overview of the typical UOC's enrollment process.

Step 1	Step 2	Step 3	Step 4
Visit Degree Landing Page	Explore Program Information	Log in to “Welcome Campus”	Select how many and which subjects
https://www.uoc.edu/es/estudios/grados/grado-ingenieria-informatica	Fill out the registration form with basic student information	Advisors may provide further information about enrollment prerequisites or answer any remaining questions	This might involve an email conversation with advisors

The first tool students encounter in the enrollment process is the Computer Science degree landing page. This page provides a comprehensive overview of the program using lists and tables to present information about the degree itself, the study plan, subjects, objectives, admission prerequisites, credit recognition, career opportunities, teaching staff and the enrollment process (refer to Figures 4.1 and 4.2). The landing page also includes a form for students to request additional information. Once completed, the form grants access to the "welcome campus" page where advisors offer personalized guidance to students.

Figure 4.1 - Example of degree landing page (structure)

Landing Page of the Computer Science Degree Curriculum (Spanish Version, 2019). Note that the current URL may no longer be valid due to website updates. However, the table format for displaying subjects remains consistent (Grado online en Ingeniería Informática | UOC, s. f.).

Plan de estudios

- Presentación
- Plan de estudios
- Objetivos, perfiles y competencias
- Requisitos de acceso
- Reconocimiento de créditos
- Salidas profesionales
- Equipo docente
- Matrícula y precio

Formamos a los informáticos del futuro.

El plan de estudios de Ingeniería informática se compone 240 créditos ECTS, que se distribuyen de acuerdo con las directrices del Ministerio de Educación.

Tipo de materia	Créditos ECTS
Formación básica	60
Obligatorias	96
Optativas	72
Trabajo final de grado	12
Total	240

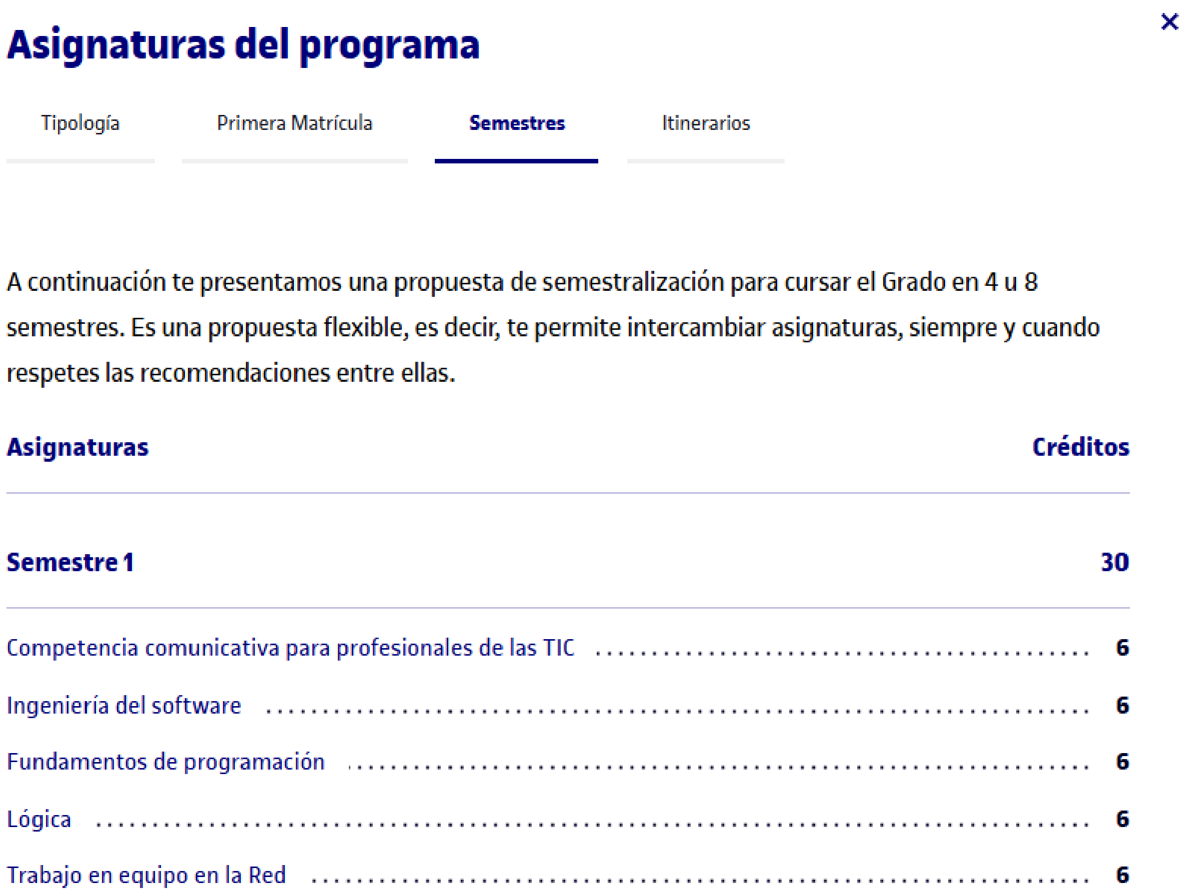
Asignaturas

- Tipología
- Primera Matrícula
- Semestres
- Itinerarios

Formación básica (60 ECTS)	Créditos
Fundamentos de programación	6
Prácticas de programación	6
Administración y gestión de organizaciones	6
Álgebra	6
Análisis matemático	6
Lógica	6
Estadística	6
Trabajo en equipo en la red	6
Fundamentos de computadores	6
Fundamentos físicos de la informática	6

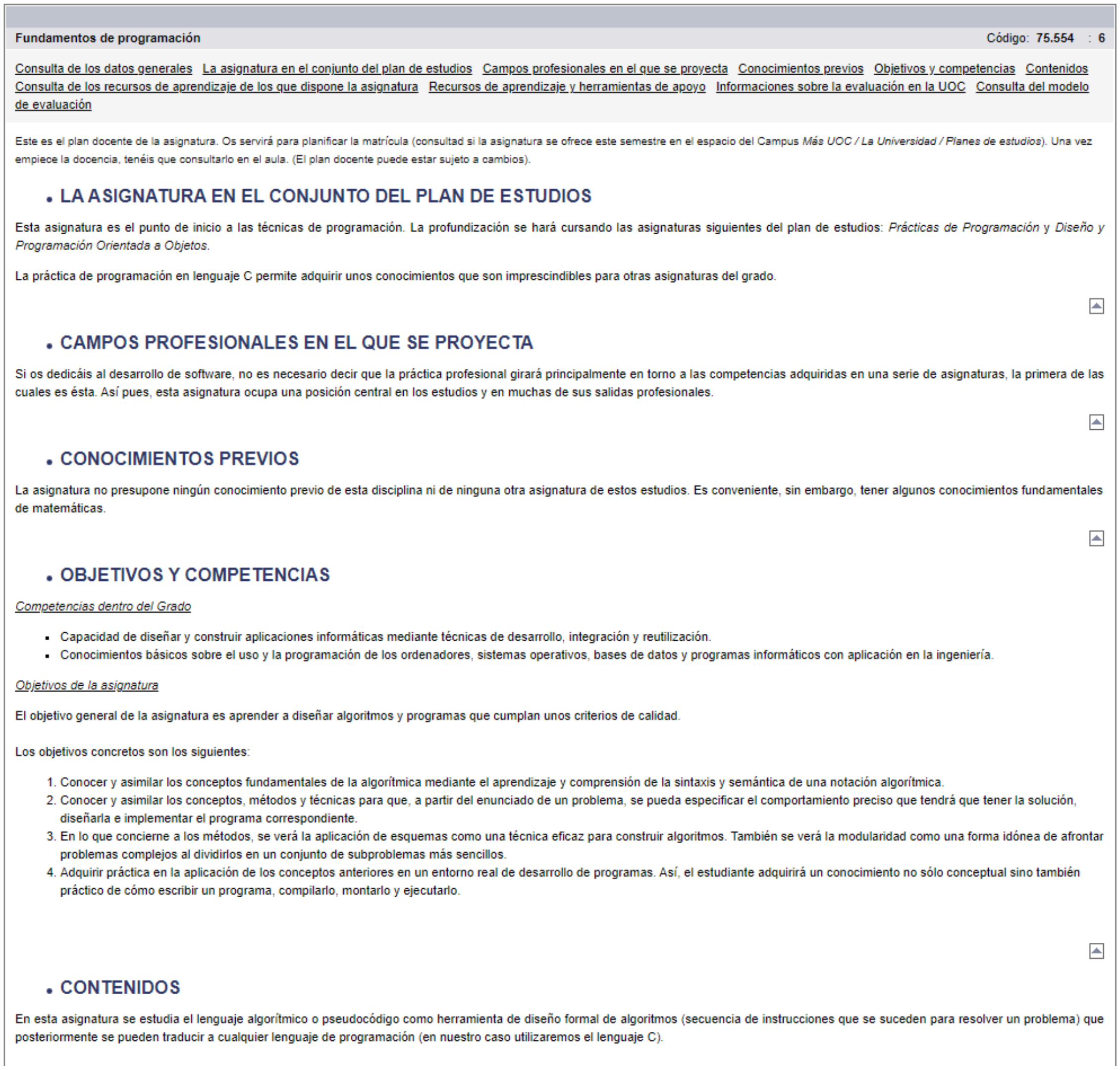
Figure 4.2 - Example of degree landing page (subjects)

Landing Page of the Computer Science Degree Curriculum (Spanish Version, 2024). Note that the current URL may no longer be valid due to website updates. In the “Primera Matrícula” *tab, the ESPRIA package subjects are displayed (González et al., 2020). The* “Semestres” *tab keeps showing subjects organised in semestres (Grado online en Ingeniería Informática | UOC).*



Upon completing all necessary procedures, students can enroll in their chosen subjects. UOC provides several resources to assist with registration beyond the degree landing page. These include dedicated subject pages (Figure 4.3) with detailed information in text and table format and the opportunity to consult with academic advisors. External sources might also be consulted during the subject research process, such as pages external to the UOC, social networks, reviews or opinions of other students or their own work or professional environment.

Figure 4.3 - Example of subject information page
Sample subject information page (Spanish Version, 2019).



Fundamentos de programación Código: **75.554** : **6**

Consulta de los datos generales La asignatura en el conjunto del plan de estudios Campos profesionales en el que se proyecta Conocimientos previos Objetivos y competencias Contenidos Consulta de los recursos de aprendizaje de los que dispone la asignatura Recursos de aprendizaje y herramientas de apoyo Informaciones sobre la evaluación en la UOC Consulta del modelo de evaluación

Este es el plan docente de la asignatura. Os servirá para planificar la matrícula (consultad si la asignatura se ofrece este semestre en el espacio del Campus *Más UOC / La Universidad / Planes de estudios*). Una vez empiece la docencia, tenéis que consultarlo en el aula. (El plan docente puede estar sujeto a cambios).

- **LA ASIGNATURA EN EL CONJUNTO DEL PLAN DE ESTUDIOS**

Esta asignatura es el punto de inicio a las técnicas de programación. La profundización se hará cursando las asignaturas siguientes del plan de estudios: *Prácticas de Programación* y *Diseño y Programación Orientada a Objetos*.

La práctica de programación en lenguaje C permite adquirir unos conocimientos que son imprescindibles para otras asignaturas del grado.

- **CAMPOS PROFESIONALES EN EL QUE SE PROYECTA**

Si os dedicáis al desarrollo de software, no es necesario decir que la práctica profesional girará principalmente en torno a las competencias adquiridas en una serie de asignaturas, la primera de las cuales es ésta. Así pues, esta asignatura ocupa una posición central en los estudios y en muchas de sus salidas profesionales.

- **CONOCIMIENTOS PREVIOS**

La asignatura no presupone ningún conocimiento previo de esta disciplina ni de ninguna otra asignatura de estos estudios. Es conveniente, sin embargo, tener algunos conocimientos fundamentales de matemáticas.

- **OBJETIVOS Y COMPETENCIAS**

Competencias dentro del Grado

- Capacidad de diseñar y construir aplicaciones informáticas mediante técnicas de desarrollo, integración y reutilización.
- Conocimientos básicos sobre el uso y la programación de los ordenadores, sistemas operativos, bases de datos y programas informáticos con aplicación en la ingeniería.

Objetivos de la asignatura

El objetivo general de la asignatura es aprender a diseñar algoritmos y programas que cumplan unos criterios de calidad.

Los objetivos concretos son los siguientes:

1. Conocer y asimilar los conceptos fundamentales de la algorítmica mediante el aprendizaje y comprensión de la sintaxis y semántica de una notación algorítmica.
2. Conocer y asimilar los conceptos, métodos y técnicas para que, a partir del enunciado de un problema, se pueda especificar el comportamiento preciso que tendrá que tener la solución, diseñarla e implementar el programa correspondiente.
3. En lo que concierne a los métodos, se verá la aplicación de esquemas como una técnica eficaz para construir algoritmos. También se verá la modularidad como una forma idónea de afrontar problemas complejos al dividirlos en un conjunto de subproblemas más sencillos.
4. Adquirir práctica en la aplicación de los conceptos anteriores en un entorno real de desarrollo de programas. Así, el estudiante adquirirá un conocimiento no sólo conceptual sino también práctico de cómo escribir un programa, compilarlo, montarlo y ejecutarlo.

- **CONTENIDOS**

En esta asignatura se estudia el lenguaje algorítmico o pseudocódigo como herramienta de diseño formal de algoritmos (secuencia de instrucciones que se suceden para resolver un problema) que posteriormente se pueden traducir a cualquier lenguaje de programación (en nuestro caso utilizaremos el lenguaje C).

Once students have reviewed the available information resources, they are ready to make an enrollment decision. A key advantage of open universities like the UOC, the Open University in the UK and UNED in Spain is the flexibility in subject selection. The UOC' s enrollment system offers minimal restrictions, with a few important exceptions:

- **Credit Limit:** Students cannot enroll in more than 40 credits per semester without special permission.
- **Subject Availability:** Students can only enroll in subjects offered during the current semester.
- **Itineraries:** To complete their degree, students must select a total of 72 credits from elective subjects. Of these, half (36 credits) must be chosen from a specific

itinerary (Hardware, Software, Computation, Information Systems, or Information Technologies), while the other half can be selected from any other itinerary.

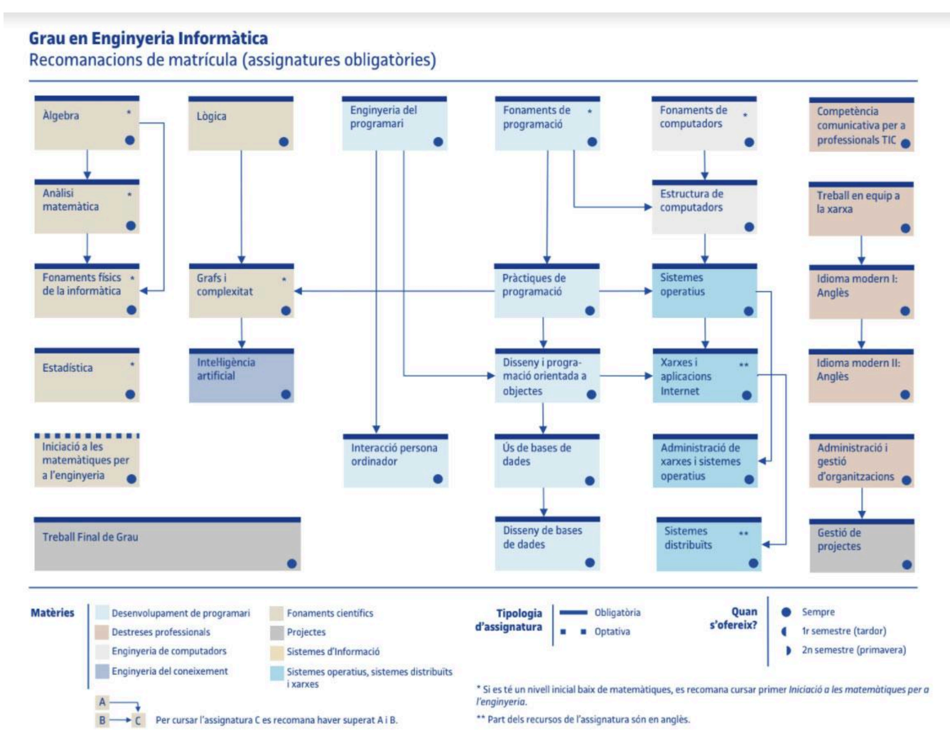
- **Prerequisite Credits:** To be eligible to enroll in the Final Degree Project (TFG), students must have successfully completed at least 80% of their required credits.

Nevertheless, these restrictions do not prevent students from choosing inadequate subject combinations, nor do they force them to follow the recommended curricular order. Students have near-unrestricted autonomy in selecting subjects or subject combinations, regardless of their suitability.

After finalizing their enrollment decisions, students can consult with their advisors to confirm their choices. The recommendation process starts when a student proposes a certain subject selection to the advisor. Upon receipt of the proposal, the advisor compares the student selection with the student academic record and other institutional resources. If the advisor finds the student's proposal suitable, the result is an immediate enrollment approval. Nevertheless, discrepancies between advisor and student necessitate further investigation, often requiring direct communication to evaluate the student’s decision-making process. Advisors offer expert guidance and answer any questions students may have. However, the final decision on the number and selection of subjects remains with the student. Therefore, students have the flexibility to modify their subject selections according to their personal preferences, and advisor consultations are not mandatory. Furthermore, students can change their final selection of subjects without further consultation.

Figure 4.4 - Diagram of dependencies between subjects

Official UOC’s diagram used by advisors and students to see the dependencies between subjects when enrolling.



Due to the flexible enrollment process described above, students can create a variety of enrollment outcomes based on their individual choices. For instance, in the semester 2019/1, more than 37,000 students took at least one subject from one official degree at the Universitat Oberta de Catalunya (UOC), from a catalog of almost 1,800 subjects scattered among 28 degrees (in two different languages). Most of these 37,000 students enrolled into one and up to five different subjects, generating more than 24,000 different enrollment patterns following a long-tail distribution, where most enrollment patterns were just taken by only one student (Rivas et al., 2021). The observed high degree of variation in student enrollment selections makes it challenging to identify recurring patterns and accurately assess the underlying motivations behind subject choices.

In order to support the enrollment process, understanding which information sources students value and how they utilize them during this procedure is crucial for developing effective enrollment tools. Similarly, identifying the factors that influence student decision making allows for the creation of a mapping of pertinent academic information. To achieve this, we employed a multi-faceted approach, including web analysis and a questionnaire (in two iterations). These two research methodologies provided significant findings.

4.2 Web analysis

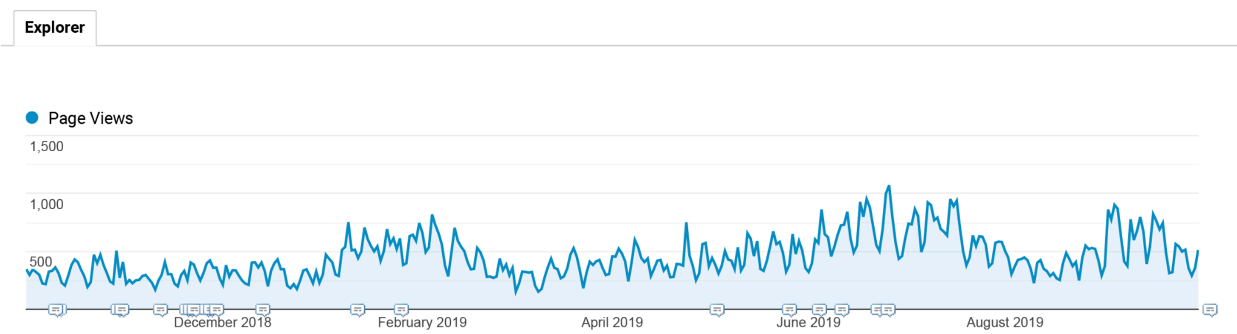
An initial approach to comprehending user behavior involved examining user activity metrics (Kaushik, 2009). In particular, analyzing page views, average time on page, bounce rate and subsequent user actions provided a valuable starting point for understanding user behavior. However, due to limitations in access to the full Google Analytics Universal metrics at the time, the UOC provided alternative data sources in the form of screenshots and information tables on user behavior flow.

The web analysis revealed that users spend the most time on web pages describing the degree structure (Figure 4.5). These pages also appeared frequently in the browsing paths users take before requesting access and information (Table 4.2). Notably, these pages had a high average page time and a low bounce rate, indicating sustained engagement. The Computer Science degree study plan's landing page appeared to be a crucial first step for users considering enrollment (Rivas et al., 2021).

Website user behavior analysis, while offering valuable insights (Kaushik, 2009), has limitations in capturing the full picture of student decision making during enrollment. Firstly, the web analytics reports used may not have comprehensively captured the target user population. Page views could have included prospective students, faculty, advisors, or other university personnel. Secondly, user website visits may not have definitively indicated enrollment intent. Furthermore, website user behavior analysis might not have provided insights into the rationale behind student subject choices. This limited the understanding of the factors influencing enrollment decisions. In addition, there may have been students who did not get information directly from the web but from other channels.

Figure 4.5 - Most viewed degree web pages

Most viewed Computer Science Degree program pages (Source: Universal Analytics).



	Page	Page Views	Unique Page Views	Avg. Time on Page	Entrances	Bounce Rate	% Exit
		164,585 % of Total: 0.39% (42,412,926)	**127,314** % of Total: 0.42% (30,253,483)	**00:02:54** Avg for View: 00:04:43 (-38.67%)	**39,123** % of Total: 0.18% (21,289,913)	**36.87%** Avg for View: 45.11% (-18.27%)	**31.03%** Avg for View: 50.20% (-38.18%)
1.	estudios.uoc.edu/es/grados/ingenieria-informatica/presentacion	**64,485** **(39.18%)**	50,311 (39.52%)	00:01:55	17,457 (44.62%)	28.41%	23.20%
2.	estudios.uoc.edu/es/grados/ingenieria-informatica/plan-estudios	**37,125** **(22.56%)**	28,839 (22.65%)	00:05:57	7,958 (20.34%)	30.64%	43.81%
3.	estudios.uoc.edu/es/grados/ingenieria-informatica/precio-matricula	**17,865** **(10.85%)**	11,659 (9.16%)	00:01:46	2,451 (6.26%)	38.49%	22.59%
4.	estudios.uoc.edu/es/grados/ingenieria-informatica/tablas-cfgs	**14,035** **(8.53%)**	10,948 (8.60%)	00:04:19	2,956 (7.56%)	41.25%	36.54%
5.	estudios.uoc.edu/es/grados/ingenieria-informatica/pago-becas-descuento	**7,063** **(4.29%)**	5,319 (4.18%)	00:03:25	594 (1.52%)	33.88%	30.20%
6.	estudios.uoc.edu/es/grados/ingenieria-informatica/estudiar-online-programa	**6,860** **(4.17%)**	6,317 (4.96%)	00:05:31	5,629 (14.39%)	71.16%	80.77%
7.	estudios.uoc.edu/es/grados/ingenieria-informatica/reconocimiento-creditos	**6,559** **(3.99%)**	4,914 (3.86%)	00:01:13	732 (1.87%)	23.45%	12.41%
8.	estudios.uoc.edu/es/grados/ingenieria-informatica/requisitos-acceso-titulacion-convalidaciones	**5,790** **(3.52%)**	4,811 (3.78%)	00:01:51	815 (2.08%)	33.18%	19.86%
9.	estudios.uoc.edu/es/grados/ingenieria-informatica/objetivos-perfiles-competencias	**1,948** **(1.18%)**	1,705 (1.34%)	00:01:40	95 (0.24%)	25.25%	13.86%
10.	estudios.uoc.edu/es/grados/ingenieria-informatica/salidas-profesionales	**1,797** **(1.09%)**	1,579 (1.24%)	00:02:05	233 (0.60%)	51.45%	25.04%

Table 4.2 - Example of paths from the landing page

Behavior flow from the landing page.

Step 1			**Step 2**		
Landing page	Sessions	% Users	Information selected by user	Sessions	% Users
Degree presentation page	44.000	100%	Study Plan	7.100	16%
			Credit validation	2,400	5%
			Enrollment requisites	589	1%
			Price	589	1%

While the analysis of quantitative data provided valuable insights into user behavior (i.e. "which" pages were visited and time spent), it lacked the ability to address the underlying motivations behind these actions (i.e. "why") (Kaushik, 2009). Understanding user goals, satisfaction with information access, and potential shortcomings in information provision remained unanswered. To address this gap and gain deeper qualitative insights, we employed a questionnaire.

4.3 Questionnaire

This questionnaire aimed to understand student preferences (Hilliger et al., 2020) for information about the Computer Science degree. Specifically how such information, if offered before enrollment, could support their subject selection decisions (James Marshall & Machun, 2012). Prior research supports the use of questionnaires to inform learning dashboard design. Studies by Corrin and de Barba (2015) and Park and Jo (2015) employed questionnaires and interviews to gather data that guided their design choices.

Our goal was to create a mapping of possible descriptive topics that students felt would be most helpful when enrolling, the role of validations and different information sources, different factors that make students choose the total number of subjects or specific subjects, students' motivations to learn and their overall opinion on the enrollment process. The questionnaire was distributed to UOC students through two rounds of interactions.

We constructed an initial iteration to gather preliminary data. Following a factor analysis of this data, we distributed a revised questionnaire in a second iteration to a larger student sample. Both iterations yielded valuable insights regarding student-advisor relationships, the time factor in subject selection, academic history, prerequisites and other relevant factors.

4.3.1 First iteration

In the first interaction, we collected information regarding students' motivations for choosing the Computer Science degree. Additionally, we explored students' current situation by asking about their enrollment history (number of semesters enrolled in and subjects enrolled in during the last semester), validated subjects and information sources used for the last enrollment selection. Furthermore, we investigated factors influencing students' decisions. This included factors considered when determining total subject enrollment, choosing individual subjects and factors that could be helpful during subject selection. Finally, we addressed student satisfaction with the enrollment process by including an open-ended question for any additional information they wished to share.

The questionnaire consisted of several question formats to gather data on student enrollment decisions. The first four questions (Q1-Q4) employed multiple-choice options to assess student motivation for choosing Computer Science, enrollment duration (number of semesters), the number of subjects enrolled in during the last semester and details about validated subjects. Questions Q5-Q8 used a 1-to-5 Likert scale to evaluate 31 factors grouped into four categories: information sources used, reasons for determining the number of subjects to enroll in, reasons for choosing specific subjects and other influential factors. Student satisfaction with the enrollment process was measured on a 1-to-10 scale (Q9). Finally, an open-ended question (Q10) allowed for feedback on the registration process. The complete questionnaire used in the first iteration is available in Annex A.1.1.

Additional information from the institutional learning record store (Minguillón et al., 2018) was also available for the participating students. Namely gender, age group, relative semester, and previous studies' level. Table 4.3 summarizes population demographics. Notice that most students were men, which is typical of any Computer Science degree (Minguillón et al., 2023), and older than traditional brick-and-mortar universities (μ=30.7 years old, σ=8.5). Approximately half of them (53.4%) had previous higher education experience.

Table 4.3 - Student's demographics

Demographics of students participating in the first iteration of the online questionnaire.

Gender	Female Male	191 1,261	13.2% 86.8%
Age group	<= 20 years old 21-30 years old 31-40 years old > 40 years old	61 776 382 233	4.2% 53.4% 26.3% 16.1%
Relative semester	1st 2nd	763 689	52.5% 47.5%
Previous studies	Special access First degree Initiated degree Finished degree	47 630 579 196	3.2% 43.4% 39.9% 13.5%
Total		1,452	100.0%

The questionnaire was sent to all students taking the Computer Science degree in their first or second semester at the UOC. The available institutional tool (Qualtrics) was used, as it is integrated into the institutional information systems for gathering data from students. Through Qualtrics, an email containing a personalized (and anonymized) link to the questionnaire was sent to each student, followed by a reminder six days later. The questionnaire was available online for a total of 12 days. A total of 1,452 students were involved in the first iteration. Of the 229 responses received, incomplete entries and those indicating a lack of willingness to participate were excluded. This resulted in a final sample of 184 usable responses for analysis purposes, representing a response rate of 12.7%. Sampling error at a 95% confidence level and maximum uncertainty (p=q=0.5) was 6.75%. Responses were weighted according to gender, age group and number of semesters, in order to reflect the targeted student demographics using the Survey R package (Lumley, 2004). As some responses had missing values, multiple imputation implemented by the MICE algorithm (van Buuren & Groothuis-Oudshoorn, 2011) was used.

Table 4.4 presents data on the number of enrolled subjects categorized by weighted participant demographics. This analysis offered valuable insights into the factors influencing student enrollment decisions at the UOC. As expected in a distance learning university, student enrollment primarily focused on two (41.7%) or three subjects (24.8%), as shown in Table 4.4. A smaller portion of students enrolled in just one subject (12.5%), while 21.0% enrolled in four, five, six or more subjects. Table 4.4 also details enrollment by student demographics. There were no significant gender-based differences in enrollment numbers. However, younger students tended to enroll in more subjects, with this trend holding true across age groups. Similarly, students in their second semester enrolled in more subjects than new students, likely leveraging successful experiences from the previous semester. Regarding prior studies, no significant differences were found overall, although students with partial or completed university experience enrolled in slightly fewer subjects. Regarding the recognition of previous studies, Table 4.4 shows that most students (85.6%) had one or more subjects that they want to be recognized and incorporated into their academic record. These subjects could have been requested or pending. On the other hand, students without validated subjects enrolled in more subjects, while students that had not decided yet enrolled in fewer subjects. This data shows that previous studies were a key factor when deciding the final number of subjects to enroll in.

Table 4.4 - Number of enrolled subjects

Number of enrolled subjects by student demographics.

		Weighted %	Number of subjects μ (σ)	Kruskal-Wallis test
Gender	Female Male	13.4% 86.6%	2.51 (1.30) 2.71 (1.22)	1.0345 $p = 0.3023$
Age group	<=20 years old 21-30 years old 31-40 years old >40 years old	2.4% 54.4% 26.8% 16.4%	**4.00** (0.99) 2.89 (1.34) 2.36 (0.86) 2.33 (1.15)	62.69 $p < 0.001$
Relative semester	1st 2nd	51.6% 48.4%	2.44 (1.06) 2.94 (1.35)	2.3761 $p = 0.01854$
Previous studies	Special access First degree Initiated degree Finished degree	6.1% 43.9% 35.0% 15.0%	2.91 (1.04) 2.61 (1.13) 2.80 (1.38) 2.52 (1.25)	2.143 $p = 0.5446$
Validated subjects	None Pending Requested	14.4% 42.0% 43.6%	**3.35** (1.25) 2.36 (0.87) 2.77 (1.42)	13.312 $p = 0.001626$
Reasons	Personal Professional Both	23.3% 39.1% 37.6%	2.60 (1.18) **3.09** (1.27) 2.52 (1.23)	6.11 $p = 0.04956$
Total		100.0%	2.68 (1.23)	

Regarding the reasons for taking a degree (students could select up to two of them), most students said it was only for professional reasons (39.1%), while a few said it was for only personal reasons (23.3%), and the remaining (37.6%) selected both possibilities. Notice that professional reasons had a positive impact on the number of enrolled subjects, as students probably needed to obtain the degree as soon as possible in order to advance their career.

Following the analysis of student characteristics, we employed an exploratory factor analysis to investigate correlations between different questionnaire items and to identify underlying thematic structures (main topics). We conducted the analysis in order to explore whether students with diverse backgrounds prioritized different factors during enrollment.

Using the weighted covariance matrix, the overall KMO index for all the questionnaire items was computed, obtaining KMO=0.79, which was reasonable as stated by (Kaiser, 1974). One of the items had a low index (Q6_1, KMO=0.46), so it was removed. A total of eight factors were found to be meaningful, according to three different criteria: eigenvalues, parallel analysis and optimal coordinates. While having eight factors may seem like a lot considering the limited number of responses, they have in fact provided interesting clues about students' habits. These factors explained 55.8% of the total variance. A cutoff threshold of 0.5 to avoid items shared by more than one factor was used. The responses collected for each factor (Q) are detailed in Annex A.1.1.

The first factor identified, labeled Difficulty (F1), combines information from items Q8_2 (pass rate for continuous assessment), Q8_3 (overall subject pass rate), and Q8_4 (percentage of students retaking the subject). This factor reflects how students perceive the difficulty of a given subject. The second factor, Advisors (F2), integrates information from items Q5_2 (advisor recommendation importance as an information source for enrollment), Q6_3 (advisor recommendation importance in determining the number of subjects to enroll), and Q7_1 (advisor recommendation importance in subject selection). This factor captures the perceived value of advisor support during the enrollment process. The third factor, Interests (F3), combines information from items Q6_7 (acquiring knowledge for professional development), Q7_2 (personal interests), Q7_3 (professional interests), and Q7_12 (the subject explores a cutting-edge topic in the professional field). This factor captures the influence of both personal and professional interests on subject selection. Factors from F4 to F8 reflect other interesting topics, but do not show conclusive results. For a complete list of questions and items, please refer to Annex A.1.1:

- Previous knowledge and competencies (F4): Combines items Q5_4, Q7_6 and Q7_7.
- Subject design methodology (F5): Combines items Q7_9 and Q7_10.
- Experience from the previous semester (F6): Combines items Q6_4 and Q7_5.
- Satisfaction and subject calendar (F7): Combines items Q8_5, Q8_6 and Q8_7.
- Degree semester organization (F8): item Q7_4.

Table 4.5 includes the most interesting factors: F1 (Difficulty), F2 (Advisors) and F3 (Interests). The most relevant data is highlighted in bold. Younger and special access students seem to be concerned about subject difficulty. Younger and students who had finished a degree rely more on the website as an information source and less on advisors. Special access students care less about their interests in certain subjects or topics. Table 4.5 shows these and other relevant factors according to such groups.

Table 4.5 - Factors influencing enrollment
Factors influencing enrollment decisions by student demographics.

		Web-advisors (-4 to 4)	Satisfaction (1 to 10)	F1 Difficulty (1 to 5)	F2 Advisors	F3 Interests
Gender	Female	0.31	7.68	3.09	3.48	3.52
	Male	0.63	7.93	2.85	3.41	3.28
Age group	<=20 years old	**0.97**	8.18	**3.69**	**3.05**	3.34
	21-30 years old	0.61	8.02	2.90	3.35	3.27
	31-40 years old	0.59	7.78	2.99	3.60	3.50
	>40 years old	0.44	7.67	2.53	3.42	3.15
Relative semester	1st	0.43	7.87	2.90	3.63	3.32
	2nd	0.74	7.93	2.87	3.20	3.31
Previous studies	Special access	0.59	7.82	**2.24**	3.62	**2.97**
	First degree	0.35	7.73	2.89	3.57	3.28
	Initiated degree	0.43	**8.44**	3.10	3.53	3.47
	Finished degree	**1.63**	**7.18**	2.63	**2.64**	3.21
Validated subjects	None	**1.09**	7.79	3.07	3.28	3.30
	Pending	0.49	7.23	2.71	3.33	3.24
	Requested	0.50	8.10	2.99	3.56	3.39
Reasons	Personal	0.58	7.97	2.90	3.35	3.42
	Professional	**0.99**	7.42	2.93	3.23	3.26
	Both	0.33	8.12	2.84	3.61	3.24
Total		0.58	7.90	2.88	3.42	3.32

Our analysis of the first interaction yielded very interesting results. Specifically, Q5 (Assess the importance of each source of information to determine your last enrollment) provided valuable information about the sources students consult to determine their enrollment choices. Surprisingly, advisors were not considered the most valuable resource (3.59, SD=0.11), but the information available in the institutional website (4.18, SD=0.09). For exploratory purposes the difference among both items was computed, which ranges from -4 (advisors preferred) to 4 (website preferred), and compared among groups.

Q6 (*Rate each factor with respect to its importance to determine the total number of subjects you have enrolled in*) was analyzed to understand the factors influencing students' enrollment decisions regarding the number of subjects. The available time for studying was the most important item for students, followed by the difficulty of the subjects. Time and difficulty were, therefore, the main reasons for determining the total number of subjects selected.

Furthermore, Q7 (*Evaluate each factor with respect to its importance when choosing the subjects in which you have enrolled*) was analyzed, in order to know why students choose each subject. Passed and validated subjects were the most important items, followed by the knowledge that students have (or think they have) about the curriculum of each subject. Students seemed less interested in subject methodology or if the subject was an innovative topic in the field.

Q8 focused on other factors students consider when choosing subjects. This information is available through the institutional Learning Record Store (Minguillón et al., 2018) but students do not have access to it. The most important item was the availability of the subject calendar, followed by the number of learning activities and subject difficulty. Again, time and difficulty are the most relevant topics for students.

We also analyzed an overall satisfaction indicator for the enrollment process. Q9: What grade would you rate this semester's registration process? In general, students were mostly satisfied (7.90 out of 10, SD=1.84), although some differences were found among groups. Younger students, students with a previously initiated degree, and students with more validated subjects (which are probably the same) are more satisfied than the rest. This finding might be attributed to the UOC's enrollment process being more guided compared to other institutions.

Table 4.6 - Open responses (study plan)
Open responses related to the study plan.

Male, born in 1978, 2nd semester, enrolled into four subjects	
Translated response (in English)	Original response (in Catalan)
"See more clearly which subjects are required or recommended to have passed before enrolling in the next one. Although this information is included in the info for each subject, it is often written in a "vague" or less specific way. It would be nice to have a diagram somewhere where you can see with arrows the relationships between some subjects and others, those that are required, those that are recommended to have studied before, etc."	"Veure amb més claredat quines assignatures son requisit o son recomanables haver superat abans de matricular-se de la següent. Tot i que aquesta informació està dins de la info de cada assignatura molts cops esta redactada de forma "vaga" o poc concreta. Estaia be tenir a algun lloc un diagrama on es vegi amb fletxetes les relacions entre unes assignatures i altres, les que son requisit, les que es recomana haver cursat abans, etc."
Male, born in 1975, 1st semester, enrolled into five subjects	
Translated response (in English)	Original response (in Spanish)
"It would be interesting to unify the information about the subjects, the type (compulsory, optional, etc.), which ones depend on having taken others, the itineraries, etc. **in one single place**. Now there are various documents that must be consulted separately to plan which subjects to enroll in."	"Sería interesante unificar la información sobre las asignaturas, el tipo (obligatorias, optativas, etc), cuáles dependen de haber cursado otras, los itinerarios, etc. **en un sólo lugar.** Ahora hay diversos documentos que hay que ir consultando por separado para planificar en qué asignaturas matricularse."

In addition, we analyzed the qualitative responses to the open-ended question. A total of 59 written open-ended responses were collected from the participants. In summary, most of the answers talked about time and difficulty of the subjects, total enrollment prices and validations. Some of the answers were really interesting and provided ideas that could be incorporated into the learning dashboard design. For instance, despite having access to a substantial amount of information related to the study plan, students appear to encounter difficulties in locating or comprehending this information (Table 4.6). Students' desire to have all registration information in one place is particularly noteworthy.

Table 4.7 - Open responses (time management)
Open responses related to time management.

Translated responses (in English)	Original responses (in Spanish)
Male, born in 1986, 1st semester, enrolled into three subjects	
"As this was my first enrollment at the UOC, I would have liked to have known the specific dates for the final exams."	"Al ser la primera matrícula que realicé en la UOC, me hubiera gustado poder saber las fechas concretas para los exámenes finales."
Male, born in 1967, 2nd semester, taking a break	
"I think that visualizing the key dates in advance, regarding the deadline of continuous assessment tests, is decisive for the correct organization of the semester by the students."	"Creo que visualizar con antelación las fechas clave, respecto a la entrega de pruebas de evaluación continua, es determinante para la correcta organización del semestre por parte del alumnado."
Female, born in 1988, 2nd semester, enrolled into one subject	
"(...) Although the estimated number of hours of weekly dedication is calculated based on the number of credits, I believe that this estimate is not very realistic, since there are subjects that, due to their difficulty in assimilating new concepts, require much more time than what is estimated."	"(...) Aunque el número de horas de dedicación semanal estimadas se calcula en función del número de créditos, creo que está estimación no es muy realista, ya que hay asignaturas que por su dificultad para asimilar conceptos nuevos, requieren mucho más tiempo del que se estima."

The analysis of student responses revealed that a simple list of subjects is insufficient for effective study planning. On the other hand, student feedback regarding the calendar highlights the importance of readily accessible activity deadlines and exam dates for effective time management. This suggests that time is a critical factor for UOC students (Table 4.7).

Student satisfaction with advisors was also found to vary. While some students report positive experiences, others suggest that communication between students and advisors could be enhanced (Table 4.8).

Table 4.8 - Open responses (advisors)
Open responses related to advisors.

Male, born in 1999, 2nd semester, enrolled into four subjects	
Translated response (in English)	Original response (in Catalan)
"I think the advisor should talk better with the student about the subjects to choose"	“Crec que el tutor hauria de parlar més bé amb l'alumne les assignatures que triar”
Male, born in 1998, 2nd semester, enrolled into five subjects	
Translated response (in English)	Original response (in Spanish)
“In my case, in my first semester I was allowed to enroll in Computer Fundamentals and Computer Structure at the same time, without any notice from my advisor that it is recommended to do Fundamentals first, so I have not been able to pass Computer Structure .”	“En mi caso, en mi primer semestre se me ha permitido matricularme en Fundamentos de Computadores y Estructura de Computadores al mismo tiempo, sin ningún aviso de mi tutora de que se recomienda primero hacer Fundamentos, con lo cual no he podido superar Estructura de computadores.”

The initial interaction analysis highlighted limitations in the current enrollment process, failing to meet the needs of all students. When considering enrollment decisions, aspects such as student-advisor collaboration, the diverse information needs of students, and the crucial role of time management in planning were found especially relevant.

4.3.2 Second iteration

Informed by the key insights extracted from the first questionnaire, we conducted a second iteration to facilitate a more in-depth investigation into two crucial areas: firstly, to achieve a more comprehensive understanding of the relationship between students and their advisors; and secondly, to further explore the information sources used by students during enrollment. Following the previous analysis, we created a revised questionnaire to address the emerging themes found in the first iteration.

In this sense, the second iteration questionnaire examined in more detail student experiences by exploring a broader range of topics. It investigated student validation of previous studies, the rationale behind their chosen number of subjects, and their assessment of the information provided on the UOC website. Additionally, the questionnaire addressed the level of attention received from the advisor during enrollment, the time students had available for studying, and the importance of enrollment costs. It further explored the significance of subject type during selection and any factors that could be helpful in subject selection. The questionnaire also examined the importance of information sources outside the UOC, such as websites, social networks, student opinions, and the students' work or professional environment. Finally, as in the first iteration, it assessed student satisfaction with the enrollment process and provided an opportunity for students to share any additional information they felt was relevant.

The complete questionnaire used in the second iteration is available in Annex A.1.2. Specifically, the questionnaire consisted of 10 questions (Q1-Q10) employing various answer formats. These included multiple-choice for the first four questions (Q1), a 1-to-5 Likert scale to assess 45 items grouped in seven questions (Q2-Q9), a 1-to-10 satisfaction scale (Q10), and open-ended responses for feedback on the registration process (Q11). Informed by the factors identified in the first interaction, this second iteration was conducted to gather further information on the validation of prior studies (Q1). Additionally, this iteration delved deeper into the rationale behind students' selection of the total number of subjects (Q2). Factors influencing this decision included: failed subjects, subject scheduling conflicts, information requested by advisors, student time constraints, and other considerations identified during the first interaction.

The second iteration also included specific questions regarding the information presented on the website study plan (Q3), advisors (Q4), the time students have available for studying (Q5), the enrollment's cost (Q6), the subject type (Q7), any additional subject-related information needs (Q8), and the students' preferred information sources (Q9).

We utilized the same methodology but the second iteration questionnaire was distributed to 4,070 students. The first iteration focused on students who had already completed a second registration (62%). In contrast, the second iteration surveyed all students in the program, regardless of their enrolled semester. Using Qualtrics, an email containing a personalized (and anonymized) link to the questionnaire was sent to each student, followed by two reminders. The questionnaire was available online for a total of 11 days. A total of 879 responses were received. Incomplete responses were excluded from the second analysis, resulting in a final sample of 699 completed responses.

The broader sample in the second iteration, included students from all semesters, which likely explains why a substantial majority of respondents (46.22%) reported having completed subject validation or being in the process. This finding might align with the profile of the typical UOC student, who may have already begun or completed some higher education courses before enrolling. Similar to the first iteration, general satisfaction with the enrollment process remains positive, with most responses on a 7-to-10 scale.

As can be seen in Table 4.9, the second iteration delved deeper into factors influencing student enrollment decisions. Notably, the questionnaire revealed that students prioritize three key aspects when determining their subject load: available time, suspended subjects, and experience from previous semesters. Interestingly, factors like the number of semesters completed and advisor information played a less significant role.

Table 4.9 - Factors influencing enrollment
Factors influencing student enrollment decisions.

Item	**Average** (1 to 5)
Previously enrolled subjects	3.95
The subjects that I have failed and must repeat	**4.29**
The validations that I have requested or plan to request	3.93
The number of semesters I have completed	3.00
The itinerary indicated in the study plan on the website	3.87
The information provided by my advisor	3.46
The time I have available to study	**4.74**
The total cost of enrollment	3.59
My experience in previous semesters	**4.29**

Table 4.10 summarizes some of the most notable factors of this iteration. More specifically, when evaluating the information presented in the UOC website's study plan, the average rating is 3.59. The most popular responses indicated that the information shown on the UOC website was sufficient to enroll and is well organized.

An analysis of student feedback on advisor attention revealed scores similar to those for the website. While students appreciated the communication procedures and assistance with adjusting the number of subjects in which to enroll, their responses indicated that they didn't consider advisors essential for enrollment decisions, as can be seen in table 4.10. Notably, responses highlighted the value of advisors as a support system, but not necessarily a decisive factor in final enrollment choices.

Time available for studies emerged as a key factor in student decision making regarding enrollment. The most popular responses included the number of hours students can dedicate to studying and the time they have available to study as key factors when determining enrollment. However, one response deviated significantly with a very low average: The information provided makes it clear how much time I should dedicate to studying before enrollment. The low average score for student responses regarding the clarity of time-related information highlights a need for improvement. This is particularly important considering students prioritize available time as the most influential factor in their enrollment decisions.

Table 4.10 - Factors according to enrollment decisions
Sample responses: factors and information sources in enrollment decisions.

Factors / Information Sources	Item	**Average** (1 to 5)
Study Plan	The information shown on the UOC website was sufficient for enrollment	3.68
	The information on the website about the degree subjects is well organized	3.56
Study Plan average rating		3.59
Advisors	The procedure and applications used to communicate with my advisor are adequate	3.96
	The advisor has helped me adjust the number of subjects for enrollment	3.85
	The advisor has been indispensable when enrolling	3.04
	I have changed my mind regarding my enrollment proposal after consulting my advisor	3.08
Advisors average rating		3.50
Time availability	The number of hours I can dedicate to studying has been an important factor when selecting the subjects for enrollment	4.70
	The time I have available to study has been the most important factor when deciding my enrollment	4.48
	The information provided makes it clear how much time I should dedicate to studying before enrollment	2.98
Time availability average rating		3.82

Table 4.11 describes the relative importance of various subject selection factors for students. Notably, prerequisites ranked highest, highlighting their critical role in student decision making. On the other hand, methodology and class size received the lowest average rating, suggesting these aspects are less influential.

Table 4.11 - Factors influencing subject selection
Factors that students take into account when selecting subjects.

Item	**Average** (1 to 5)
I have taken into account the previous necessary or recommended subjects when enrolling	4.38
The most relevant previous subjects	3.97
The methodology of each subject (use of debates, group work...) has been important when enrolling	2.88
The number of students in the classroom	1.87

As a summary of the rest of the questions analyzed, the cost of enrollment appears to be a well-understood factor for students. The registration process clarifies costs and surcharges for failed subjects are considered. On the other hand, external information sources received generally low average ratings. Student reviews and opinions were valued the most, while social networks were the least valued source.

Once more, the answers to the open question were also reviewed. A total of 193 written open-ended responses were collected from the participants. In summary, most of the answers talked about time assessment, costs, satisfaction, subject difficulty, UOC's website, validations, advisors and data visualization. Some of the answers were really interesting and provided ideas that could be incorporated in the learning dashboard design.

Student feedback on the UOC study plan highlighted a key request: a centralized location for accessing and reviewing all plan information. Students also emphasized the need for simplification, particularly within teaching plans, and improved information organization. Additionally, providing more details about each subject, rather than presenting a single, uninformative list, was identified as an area for improvement (Table 4.12).

Table 4.12 - Open responses (study plan, 2nd iteration)
Open responses related to study plan (second iteration).

Translated responses (in English)	Original responses (in Spanish)
Male, born in 1975, 2nd semester, enrolled into five subjects	
"The itinerary options and subject information are difficult to consult during the registration process. There are several separate documents that must be compared in order to decide which subjects to enroll in."	"Las opciones de itinerario e información de las asignaturas son difíciles de consultar durante el proceso de matriculación. Hay varios documentos separados que hay que ir cotejando para poder decidirse por las asignaturas a matricularse."
Female, born in 1995, 1st semester, enrolled into four subjects	
"The teaching plans are somewhat cumbersome and difficult to read. (...)"	"Los planes docentes son un tanto engorrosos y difíciles de leer. (...)"
Male, born in 1990, 3rd semester, enrolled into five subjects	
"It would be nice to have information about the semester in which the subject is located or to have the option to order them by semester, instead of having a long list with all the subjects available for enrollment. (...)"	"Estaría bien tener información acerca del semestre en el que se encuentra la asignatura o tener la opción de ordenarlas por semestre, en lugar de tener una lista larga con todas las asignaturas disponibles para matricular. (...)"
Male, born in 1989, 3rd semester, enrolled into three subjects	
"I would like the curriculum to have an option to see all the mandatory subjects ordered by semester for that specific itinerary. (...)"	"Me gustaría que en el apartado del plan de estudios hubiese una opción para ver todas las asignaturas obligatorias y ordenadas por semestres para ese itinerario en concreto. (...)"

Another common request is for a more user-friendly interface to review pending subjects (Table 4.13).

Table 4.13 - Open responses (pending subjects, 2nd iteration)
Open responses related to pending subjects (second iteration).

Translated responses (in English)	Original response (in Spanish)
Male, born in 1975, 14th semester, enrolled into one subject	
"For me, the easiest way to enroll or select subjects would be to be able to see which subjects I have pending in an easy way. At least, remove those that I have already passed from the list of pending subjects."	"Para mi, lo más fácil para poder realizar la matrícula o seleccionar las asignaturas, sería poder ver qué asignaturas tengo pendientes de una forma fácil. Al menos, quitar de la lista de asignaturas seleccionables las que ya he superado."

Student feedback regarding time representation highlights the importance of both the number of exercises and their corresponding deadlines. Notably, students indicated that these calendars, even if indicative, could be a valuable resource (Table 4.14).

Table 4.14 - Open responses (time management, 2nd iteration)
Open responses related to time management (second iteration).

Translated responses (in English)	Original responses (in Spanish)
Female, born in 1998, 3rd semester, enrolled into two subjects	
"(...) In summary: to improve the enrollment process I would like to have a simple outline of each subject, easily accessible, with clear deadline dates and a better approximation of the hours necessary to pass the subject."	"(...) En resumen: para mejorar el proceso de matrícula me gustaría contar con un esquema sencillo de cada asignatura, fácilmente accesible, con la fechas de entrega claras y una mejor aproximación de las horas necesarias para superar la asignatura."
Male, born in 1976, 12th semester, enrolled into two subjects	
"In all this time at the UOC, I have still not been able to see the PAC deadline calendar for the subjects I would like to enroll in. Although it is true that the calendar may undergo changes for various reasons, it would be interesting to have the deadline dates to anticipate possible overlaps, etc. (...)"	"En todo este tiempo en la UOC, todavía no he sido capaz de ver el calendario de entregas de PACS y Pracs de las asignaturas que quiero matricular. Si bien es cierto que el calendario puede sufrir cambios por diversas razones, sería interesante disponer de las fechas de las entregas para prever posibles solapamientos, etc. (...)"
Translated response (in English)	Original response (in Catalan)
Male, born in 1993, 2nd semester, enrolled into four subjects	
"The amount of PACS/Practical exercises that must be completed in the subject before enrolling should be provided in an easy and visual way. Even if dates are indicative."	"S'hauria de facilitar d'alguna manera fàcil de visualitzar, la quantitat de PACS/Pràctiques que s'han de realitzar a l'assignatura abans de matricularte. Ni que sigui una dada orientativa."

Positive sentiment surrounded advisors in student feedback. However, some students expressed a need for advisors to have better access to information on subjects, validations, and, as discussed earlier, deadline schedules.

Table 4.15 - Open responses (advisors, 2nd iteration)
Open responses related to advisors (second iteration).

Translated response (in English)	Original response (in Catalan)
Male, born in 1984, 1st semester, enrolled into five subjects from two different degrees (two of them from Computer Science)	
"In my experience, I have to say that I have nothing against advisors, on the contrary, they are attentive people with a correct and appropriate behavior, but when I really had doubts about validations and the possibility of doing two degrees at the same time and validating subjects in order to minimize costs and credits they didn't help me to solve it and I had to study how to do it myself because advisors do not have that information."	"Sota la meva experiència he de dir que no tinc res en contra dels tutors al contrari son gent atenta i amb un tarannà correcte i adient però quan realment he tingut dubtes de convalidacions i possibilitats de fer dos graus en paral·lel i anar convalidant assignatures per tal de minimitzar costos i crèdits no m'han ajudat a solucionar-ho i he hagut d'estudiar com fer-ho jo mateix perquè els tutors ho desconeixien."
Translated response (in English)	Original response (in Spanish)
Male, born in 1974, 10th semester, enrolled into one subject	
"One of the questions I ask the advisor in each enrollment process is how the PEC and PR are organized throughout the semester. (...)"	"Uno de las preguntas que hago al tutor en cada proceso de matrícula es, como se organizan las PEC y PR a lo largo del trimestre. (...)"

Similar to many online educational institutions, the UOC enrollment process faces limitations. With this research, we aim to analyze these limitations and identify potential areas for improvement, while acknowledging that a complete solution may not be achievable within this study. By doing so, a deeper understanding of the process can be gained and actionable improvements can be proposed. For example, the analysis of student interactions across the questionnaire highlights the need for a two-pronged approach:

1. **Enhanced UOC Website Study Plan:** Developing a user-friendly interface for the UOC website's study plan is crucial. This new interface should prioritize presenting comprehensive information in a way that empowers students to make informed enrollment decisions.
2. **Improved Advisor Information Tools:** Equipping advisors with better informational tools is equally important. This might allow them to effectively address student needs throughout the enrollment process and foster stronger student-advisor relationships.

The new interface for the study plan should prioritize the factors students identified as most important:

- Time available for studying
- Student experience in previous semesters
- Validated subjects
- Subject prerequisites
- Subject difficulty
- Deadline schedule overlaps between subjects
- Subject popularity

On the other hand, before developing a new learning dashboard prototype, we considered implementing a recommendation system. This system would integrate the factors identified through student feedback and historical enrollment data available at the UOC. By analyzing the system using simulations (available in Chapter 5), new data could provide further enrollment considerations and trends that the questionnaire iterations have not highlighted.

4.4 Summary

This chapter describes the UOC enrollment process, examining its distinct phases, the information sources students utilize and any unique aspects specific to the UOC. Furthermore, we have reviewed the findings from two complementary investigations: a web analysis and a two-iteration student questionnaire.

The web analysis included the review of user activity metrics. Although the analysis of quantitative data provided valuable insights into user behavior, it lacked the ability to address the underlying motivations behind these actions. Whereas, the two-part questionnaire allowed for a deeper understanding of students’ informational needs. Based on the results of this previous analysis, we can address the first research question of this thesis: *Which information is key for students when taking enrollment decisions in higher education official degrees that allow some flexibility?* The following factors emerged as crucial for enhancing students' decision making during enrollment: time available for studying, previous semester experience, validated subjects, prerequisites, subject difficulty, deadline overlaps, and subject popularity.

Building on these findings, we are able to map the academic information crucial to the enrollment process. However, simply knowing what is important to students is not enough. Students' understanding of this information is crucial for them to make informed decisions. This could be achieved through the development of a learning dashboard that integrates a recommendation system.

Time available for studies emerged as a primary factor influencing student choices, followed by their experience with subjects in their last semester. Online higher education students receive information in different formats and at different times. This can cause time management issues, so this new prototype could help students better manage their time (Song et al., 2004). Furthermore, student preferences regarding information for subject selection highlight the importance of scheduling. The availability of activity and test schedules should be a key element in designing the learning dashboard (Tabuenca et al., 2015). Time management is further impacted by the number of subjects enrolled in. A subject learning dashboard should consider this by discouraging students, particularly in their first semesters, from enrolling in an excessive number of subjects.

Student feedback also highlights the importance of clear information regarding subject prerequisites. Many students expressed a desire for a section that visually represents their degree path, including required prior knowledge and enrollment dependencies.

One of the most remarkable results that requires further study is the relationship between the students and advisors during enrollment. Students seem to rely more on the website information than on advisors. As stated by Schumacher, students' self-regulation is considered a key factor for success in higher education (Schumacher & Ifenthaler, 2018). Nevertheless, we need to address advisors' interventions when enrolling. The analysis of data gathered in the questionnaire has made us question if the prototype to be developed should only focus on students or could also become a support tool for advisors, in order to improve their interventions (Simpson, 2004).

We address all of these issues in the following chapters of this thesis. In Chapter 5, we explore how the student information needs highlighted in this chapter can be appropriately showcased to assist students and advisors in their enrollment decision-making processes. The potential solution we explore involves adding all of the students' information preferences to a learning dashboard that integrates a recommendation system. In Chapter 6, we investigate the extent to which this learning dashboard influences enrollment decisions made by students and advisors. The evaluation we present in this chapter assesses whether the information shown has served to improve the UOC enrollment process.

Chapter 5
Learning dashboard development

This chapter details the development of the learning dashboard to enhance any open online university enrollment process. This process involved some design proposals, the creation of a first draft of a recommendation system (a subsystem of the learning dashboard) and the fine-tuning of its parameters by means of simulations. As for the learning dashboard itself the process involved an initial proof of concept evaluated through student interviews, the development of the first fully functional prototype and a preliminary validation through advisor interviews, before the final evaluation described in the following chapter. We describe the results of every iteration, the key modifications made throughout, and a synthesis of the research findings. Finally, as a result of this process, we will address the second research question of this thesis: *How can information be appropriately showcased to assist students and advisors in their enrollment decision-making processes?*

5.1 Introduction

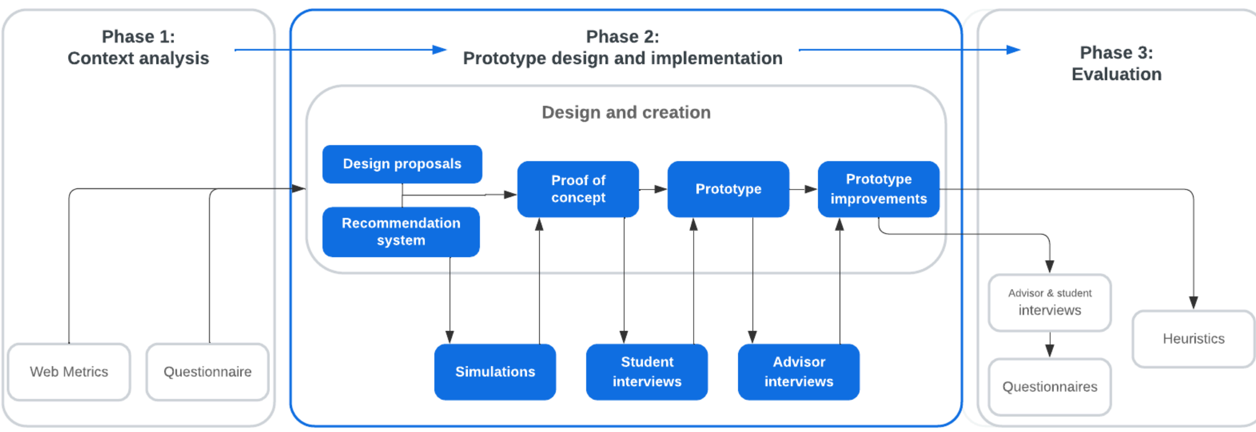
In Chapter 4 the presentation of degree curriculums at open online universities were described as simple subject lists. Analysis of web traffic data and student questionnaires revealed this approach to be inadequate for informed enrollment decisions. This transition from a basic, traditional format to a visual representation with multiple layers of information presented a significant challenge. Our aim was to create a visual representation of the curriculum that clearly showed students the information they need to make informed decisions. The qualitative study identified key student information needs, such as available study time, prior academic experience, completed subjects, prerequisites, subject difficulty, scheduling conflicts between subjects, and subject popularity. This preliminary research provided valuable data that was later applied to the development of the learning dashboard.

We followed the research process of Oates et al. (2006), focusing on developing new IT related products such as constructs, models, methods or installations. This model emphasizes the concept of learning by doing and follows an iterative process with three distinct phases: strategy development, data generation and data analysis. As part of this research process, different design proposals were developed leading to a first recommendation system and a proof of concept being created. The data generation phase involved performing simulations and conducting several informal student interviews. After which, the prototype was created and a round of advisor interviews were performed in order to improve it. To validate the entire creation process, a qualitative study with advisors and students was undertaken, which will be described in Chapter 6 of this thesis.

As shown in Figure 5.1, the project's various phases are interconnected. Chapter 4 provides a detailed explanation of the initial data generation process, which involved website metric analysis and a questionnaire (Rivas et al., 2021). Insights from this initial phase influenced the later design process and final prototype, by providing several factors crucial for enhancing student decision making during enrollment. These factors were also used in several design iterations. The initial iteration involved the development of various design proposals (described in Section 5.2) concurrently with the creation of the engine for the subject recommendation system (Section 5.3). This facilitated the creation of a proof of concept which was used as a starting point for experimentation (Section 5.4). The experimentation phase included simulations to generate quantitative data and conducting informal student interviews to gather qualitative data. The insights derived from this process were then incorporated into subsequent versions of a more comprehensive prototype: a learning dashboard that incorporates the subject recommendation system. During the second iteration, the prototype was developed (Section 5.5) which was subsequently evaluated through testing with advisors. Formal interviews were conducted with the advisors and they were given the opportunity to test the new tool. These interviews yielded a significant list of changes that were implemented in the learning dashboard in preparation for the final qualitative study.

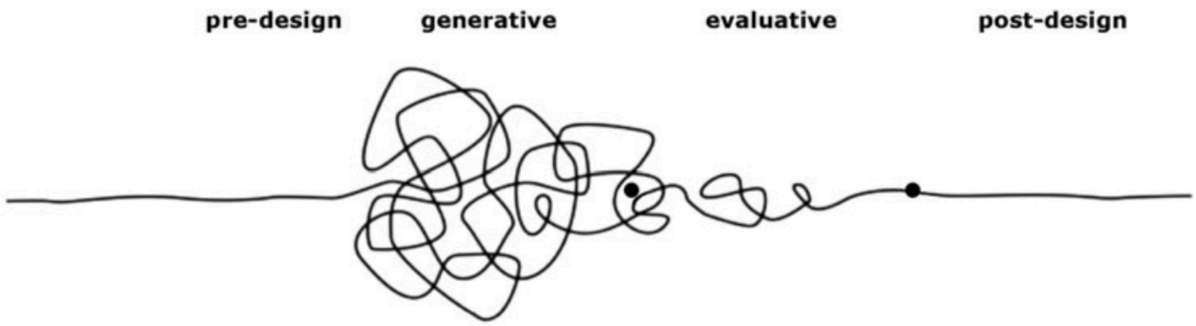
Figure 5.1 - Research process (phase 2)

Research process inspired by Oates (2006). The graph presents different design phases and their connections.



The design of the prototype demonstrably benefited from the data generated by its potential users. User-centered design is a broad term encompassing design processes where end users influence the design's development (Abras et al., 2004). All of the phases and interactions described above can be considered part of the design process, as activities were undertaken to determine requirements (within the research process), establish general directions (during the strategy phase), evaluate the design (through usability testing) and observe the use of the final prototype (Sanders & Stappers, 2014). As highlighted by these authors, pre-design research prioritizes understanding the broader experience context, while post-design research focuses on user experience with the final product. Following these principles, generative design research methods were employed, leading to the development of various prototype versions. Additionally, evaluative research was integrated throughout the different interactions within the subsequent design processes, as illustrated in Figure 5.2. Consistent with Sanders and Stappers (2014) this process adopted an iterative approach, where the conclusion of each design and analysis phase triggered the initiation of a new cycle, as depicted in Figure 5.1.

Figure 5.2 - Design phases
Phases of the design process according to Sanders and Stappers (2014).



5.2 Design proposals

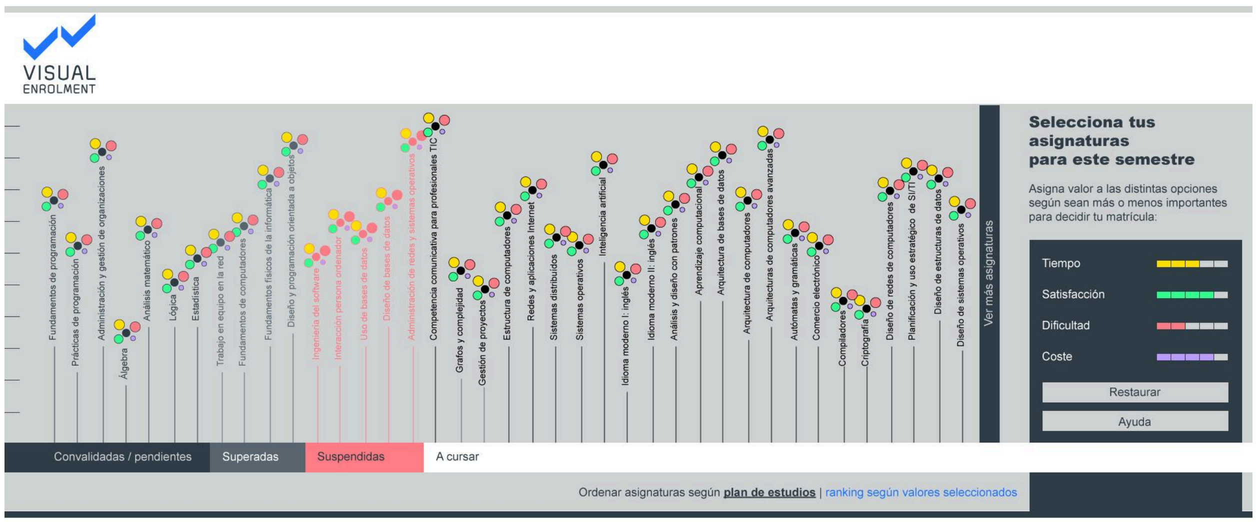
Data visualization, particularly in the form of learning dashboards, has been employed in educational settings to facilitate comprehension of large datasets. As outlined in Chapter 2 of this thesis, numerous learning dashboard projects have been undertaken by other researchers. However, a recurring challenge identified in many of these projects was the difficulty in selecting the most appropriate criteria for effective application of data visualization in student learning experiences (Duval, 2011; Schwendimann et al., 2017). To address this challenge, design proposals were created taking into account the information presented in Chapter 4 of this thesis.

We aimed to design a tool that was different from traditional subject presentation methods, exemplified by the list in Figure 4.1. These list structures have been inherited from university enrollment books, subsequently migrating to university websites. Even more innovative learning dashboard projects, such as the one depicted in Figure 2.14, often continue to utilize similar list formats (Chou et al., 2017). Another design challenge involved avoiding the use of classic static visualizations, such as bar charts or line graphs, which are commonly employed in many learning dashboard projects (Leony et al., 2012; Schwendimann et al., 2017). Our goal was to develop a representation that was not only informative but also interactive, allowing for the integration of multiple information layers in a single view. Within the aforementioned design and creation process, various design proposals were explored and ultimately discarded. A complete record of the proposals devised in this stage is included in Annex A.2.

One of the initial design proposals, inspired by the OECD (Organisation for Economic Co-operation and Development) Better Life Index (Figure 5.3), incorporated multiple information layers for student interaction (Rivas et al., 2021). The OECD Better Life Index visualization (OECD Better Life Index, s. f.) offers users an interactive tool to explore well-being across different countries. Users can assign importance weights to various factors like housing, income, education, and environment by means of a set of sliders. These weightings dynamically influence the visualization, which presents a ranked list of countries based on user-defined priorities. Previous studies on this type of data visualization (Balestra et al., 2018) have shown that users prioritize different criteria, with some factors being more influential in decision making than others. Analogously, replacing countries by subjects, students could create a personalized data visualization of their subject enrollment options and academic record. They could assess the relative importance of factors like time commitment, satisfaction ratings, difficulty level, and subject cost by allocating importance to these factors using sliders. Inspired by the research of Balestra et al. (2018), we will employ simulations to analyze the influence of the factors designated by the slider settings. The visualization also grouped subjects into categories such as validated, passed failed or subjects available for enrollment in order to effectively display the student's progress within their degree program. Despite its visual appeal, this proposal encountered several issues. Firstly, although visual, it was still a list format that had to be read sequentially. Secondly, the initial visualization appeared to prioritize a single "best subject" for enrollment, which was not aligned with our objective. Instead, the visualization should have focused on highlighting subject groups that, when combined, represent a coherent enrollment strategy for each individual student. Nevertheless, the use of sliders seems appropriate for indicating the relative importance of each factor.

Figure 5.3 - Better Life Index data visualization

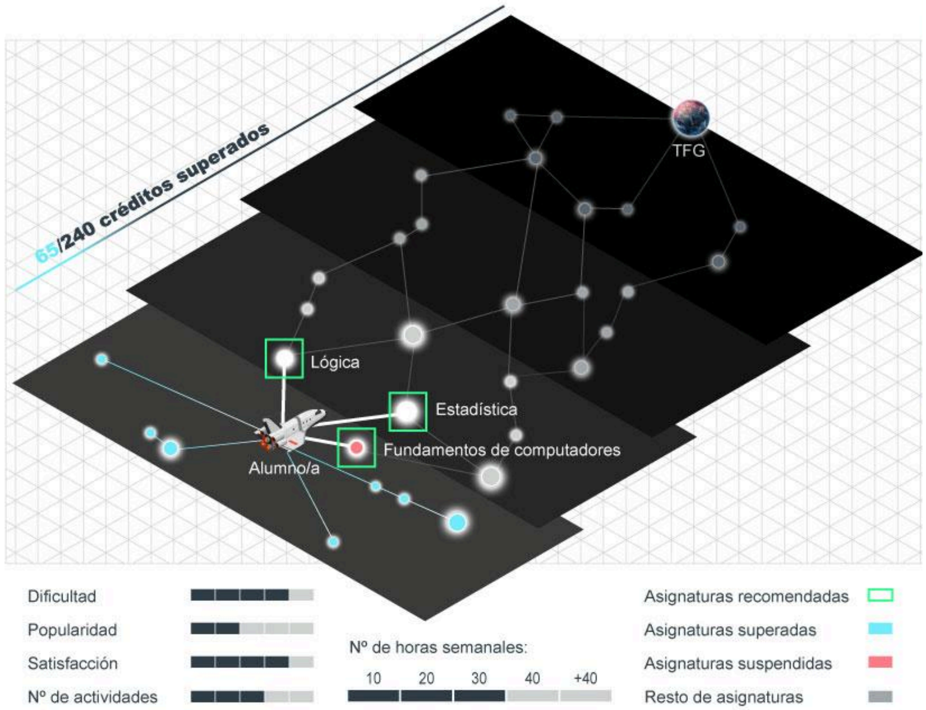
Better Life Index inspired design proposal. In the original data visualization the user can rate different topics according to their importance, and therefore modifying the order of the elements.



In another design iteration, we explored visualizing the degree program as a journey (Figure 5.4). This analogy resonated as students begin at a starting point and ultimately reach a destination (such as the degree's capstone project, TFG acronym in Spanish). The visualization concept resembled a star map, allowing students to view all their subjects represented as stars. Once again, students could personalize the visualization by assigning values to various factors like difficulty, popularity, student satisfaction, number of required activities, and weekly workload. By adjusting these values, students could dynamically reposition subjects based on their preferences. Subjects positioned closest to the spaceship would be considered the most suitable options for enrollment. However, this metaphor was ultimately discarded as it presented some limitations in fulfilling the design requirements. Unlike a physical trip where simultaneous presence in multiple locations is impossible, students can select and enroll in a maximum of six subjects concurrently. Therefore, this visualization might be misleading as it is a step-by-step presentation. For additional examples of these early design attempts, see Annex A.2.1 (Figures A.1–A.4).

Figure 5.4 - Design proposal (spaceship theme)

Spaceship inspired design proposal. Users visualize the degree as a star map and the subjects are destinations they can reach. The proposal is not appropriate since many students select several subjects in each enrollment.



This realization underscores a core concept of this thesis: taking a higher education degree is not a linear process of completing subjects one after another. This fact is crucial for the development of any visual representation related to the enrollment process. Furthermore, there are several other considerations related to the particular characteristics of the enrollment process that must be taken into account, such as:

- Most subjects are mandatory, with some electives offering some choice.
- Some electives are only available in one semester (Spring or Fall).
- While the order in the study plan may not be strictly enforced, it is generally recommended.
- Some subjects are prerequisites to others.
- Subjects cannot be selected more than once unless a student fails them.
- There is a maximum number of subjects that can be enrolled in at the same time.

These factors not only impact the visualization of information, but also the recommendation process itself. This highlights a crucial distinction between subject recommendation and entertainment recommendation platforms like Spotify, Netflix, YouTube or TikTok, as we have seen in Table 2.1. The key difference lies in the number of items recommended at any given time. Unlike in these entertainment platforms, where users consume items sequentially, subject selection often involves choosing a limited set of subjects to be taken concurrently under a set of constraints.

Figure 5.5 - Map based table games

Top figure shows a World Risk map with color-coded country ownership. Bottom figure shows a Catan game map where player status is visualized by colored pieces and positioning.

Following careful consideration of these factors, the concept of presenting the degree program as a map was ultimately selected. A linear journey was not the intended representation; instead, the focus was on visualizing each student's position within a map. This approach mirrors the experience of board games like Risk or Catan (see Figure 5.5), where players advance by strategically conquering adjacent territories based on their starting positions. By using this metaphor, we could depict progress towards the end of the degree, while also allowing for the recommendation of adjacent subjects. The design should prioritize the student's ability to visualize their entire degree program at a glance. Their academic record should be incorporated into the map, allowing users to distinguish the subjects closest to those already completed. This approach aimed to shift the perception of the degree away from linear subject enrollment and towards a progress visualization. Consequently, subjects considered most suitable for enrollment should be positioned in close proximity on the map. In other words, the relative positioning of subjects is determined by their suitability for concurrent enrollment. Although the initial map could be identical for all students, it becomes personalized upon loading individual student records. Furthermore, the map may be dynamically distorted based on the criteria considered relevant by each student, but not as a cartogram[1]. In our map, the criteria relevant to each student will change the distance between subjects, not the size of their area.

[1] A cartogram is a map where the size of geographic areas is distorted to represent a specific statistical variable («Cartogram», 2024).

In constructing the proof of concept, several factors needed to be considered. Firstly, the recommended subjects must demonstrate coherence with the student's past academic record. Secondly, the selected subjects should exhibit coherence with one another. The data concerning students collected in Chapter 4 of this thesis also required a visual representation. Interactivity was identified as a critical aspect of the visualization. Users needed to be empowered to select the relative importance they assign to different parameters, similar to the functionality offered by the OECD Better Life Index shown in Figure 5.3. Consequently, the map has to be dynamically updated to reflect the user's selections. In essence, users are actively involved in shaping their own personalized map. The map needed to clearly differentiate between previously passed or discarded subjects, failed subjects, and potential subjects yet to be enrolled in. This distinction aligns with the metaphor of "conquering the degree" by enabling students to identify a coherent pathway for progression in the upcoming semester. Additionally, the map's design should accommodate the visualization of other relevant data through the use of different information layers, following Schneiderman's mantra: *Overview first, zoom and filter, then details-on-demand* (Shneiderman, 2003).

Following this stage, the development process diverged into two distinct workstreams. On the one hand, creating the recommendation system responsible for subject placement on the map, and on the other hand, designing the visual representation of the map metaphor. While both tasks were conducted concurrently, the development and experimentation of the recommendation system will be explained first (Section 5.3), followed by the creation and experimentation of the proof of concept (Section 5.4). As we will see in the following sections, the data collected when experimenting with the recommendation system influenced the design of the proof of concept, since some of its features could be predetermined and thus simplified.

5.3 Recommendation system

The initial idea for the recommendation system was to enable students to grasp the degree structure through a quick visual inspection. Rather than employing a rigid sequential representation of time (i.e. sequence of subjects) as shown in Figure 5.3, our approach strives to present time in a more organic manner. As aforementioned, a map served as the chosen visual metaphor to achieve this. Essentially, subjects that can be taken concurrently should be positioned in proximity, while those not to be taken together should be placed at a distance from one another. In contrast to the work by Castells et al. (2020), this method aimed to avoid imposing absolute subject positioning. Instead, subjects were envisioned as part of a two-dimensional map where each subject became a region surrounded by neighboring subjects. Firstly, we ensured the explainability of the recommendation input by using student records, subject calendars, the degree curriculum and subject prerequisites. Secondly, we ensured explainability of the recommendation process by displaying the degree as a map and recommending subjects closer to the ones the student has already passed. Finally, we ensured the explainability of the recommendation output as students could easily understand the rationale behind the suggestions presented to them as they could visualize on the map. By taking into account these aspects, we aim to create a recommendation system that is not only effective but also transparent and user-friendly.

Recent works propose a similar framework, as illustrated in Figure 2.15 (Ma et al., 2024). The recommendation system involves the following steps:

1) Create an initial default map for visualizing the degree structure taking into account student records, subject calendars, the degree curriculum and subject prerequisites.
2) Visualize a student's position within the degree (i.e. map) showcasing their student record.
3) Distort the map according to the student's criteria.
4) Recommend the closest subjects “to be conquered” taking into account already passed subjects.

Subject placement within the two-dimensional space was conceptualized as a repulsive force acting between each subject pair. The magnitude of this force is influenced by various criteria. For instance, known subject combinations that result in student failure when enrolled concurrently should be positioned far apart on the map. Conversely, subjects that can be taken together without any negative consequences could be positioned in closer proximity. A similar logic applies to other factors. For example, subjects with prerequisites or overlapping activities should be positioned further apart. To achieve this separation, we calculate a partial distance for each factor, and these partial distances are then combined to determine the final relative distance between subjects. A linear combination of partial distance matrices was used to calculate the total distance between each pair of subjects, while each partial matrix represented the distance between two subjects based on a specific criterion. This approach allowed for the flexible weighting of each matrix during the combination process.

Figure 5.6 - Dimensionality and distance representation

Impact of dimensionality on distance representation. Dimensions preserve the relative distance between subjects.

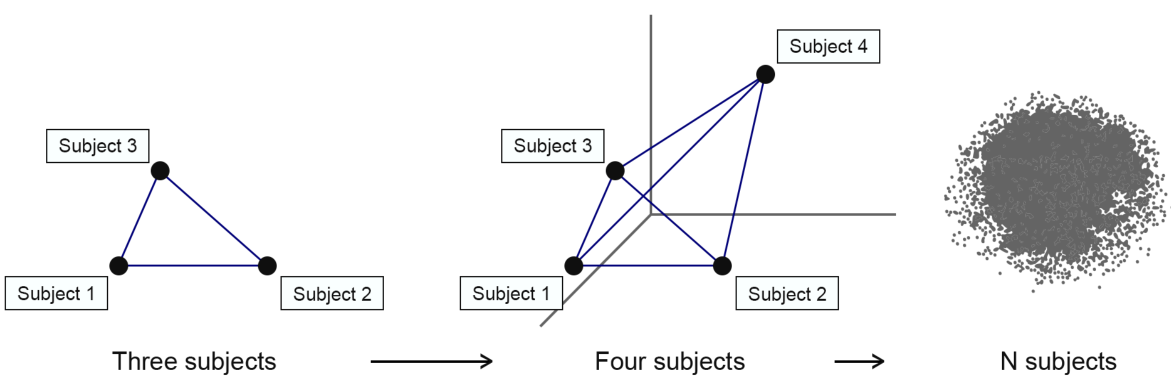
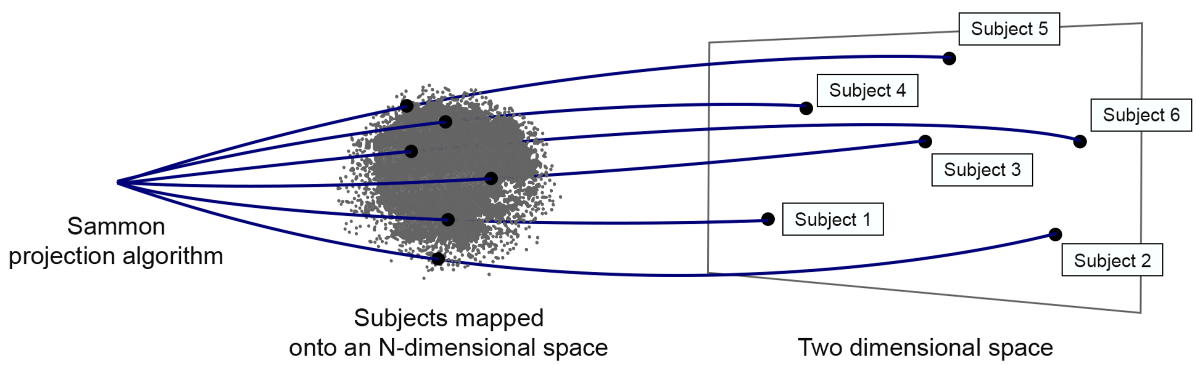


Figure 5.6 shows the process of positioning N subjects in an N dimensional space, trying to fulfill specific constraints. Suppose that we have three close subjects, Subject One, Subject Two and Subject Three. When adding Subject Four, suppose that we want it close to Subject Three but far from Subjects One and Two. In a two-dimensional space, it is impossible to maintain the required relative distances between subjects. Therefore, as we introduce more subjects, adding more dimensions might be necessary to accurately represent the desired relative distances between them.

Due to the limitations of computing all subject positions in two-dimensional space, an alternative approach was proposed for subject placement on the map. This method involves conceptualizing an N-dimensional space, where N represents the total number of subjects. Within this space, subjects are separated by adjusting the distances between each pair based on the aforementioned criteria and combining all partial distances in a single distance matrix. Once separated in the N-dimensional space, the subjects are projected onto a two-dimensional map using a technique that preserves relative distances, as represented in Figure 5.7. Among others, Sammon's projection (Sammon, 1969) was selected for this purpose due to its computational efficiency and ability to maintain these distances effectively, unlike other methods that may introduce artificial geometric structures such as circles or spirals. Other methods, such as t-SNE (van der Maaten & Hinton, 2008), were not considered due to their high computational cost, which could interfere with the use of an interactive application.

Figure 5.7 - 2D projection from N-dimensional space
Two-dimensional projection of subjects from an N-dimensional space applying Sammon algorithm.



5.3.1 Map creation

The initial map was created using historical data on student academic records. In this sense, this is similar to typical collaborative filtering recommendation systems that use data from previous users. Enrollment data for a Computer Science degree was extracted from the institutional learning repository store (Minguillón et al., 2018). This data encompassed student enrollments between the academic years 2010-2011 and 2019-2020. A total of 10,957 students participated in 42,889 enrollments, resulting in 10,409 distinct enrollment patterns across 695 unique subjects offered by the university. It is noteworthy that 7,418 enrollment patterns occurred only once, highlighting a long-tail distribution, that is, flexible enrollment leads students to make a wider range of subject selections. With the aim of developing a realistic recommendation system, data from students enrolling in 7 or more subjects (less than 1.1% of students) were excluded. Additionally, subjects with enrollments below 100 were removed from consideration, resulting in a focus on the 54 most popular subjects.

This data comes from the institutional LRS (Minguillón et al., 2018) and it is not available to students or advisors, although it has been previously used in exploratory data visualizations (Blasco-Soplón et al., 2015). This historical data provides hidden and relevant information such as subject popularity, co-enrollment failure rates, and scheduling overlaps between subjects. Degree curriculum was used to determine subject prerequisites. Taking into account all the data available, relative partial distance matrices D_C between each subject pair (i, j) were calculated as follows (the distance is zero for the case i=j):

- D_S Semester Organization
  Subjects that the degree's semester organization dictates should not be taken together should be positioned far apart (i.e., separated) in the visualization. This relative partial distance ranges from 0 for pairs of subjects that can be taken in the same semester to 1 for subjects such as introductory subjects and the capstone project.

- D_P Popularity
  Subjects that students do not typically take together should be positioned further apart. This factor partially overlaps with the previous factor (semester organization) and takes into account previous students' enrollments. This is similar to collaborative filtering algorithms, which recommend items (like songs) based on the preferences of users with similar consumption patterns. For a given pair of subjects, it is computed as 1 minus the estimated probability of taking such a pair among all the possible combinations. Therefore, it is 1 for those pairs of subjects that have never been taken at the same time.

- D_D Difficulty
  Subjects with a high probability of resulting in failure when taken concurrently should be positioned far apart. This approach also aligns with collaborative filtering algorithms, but instead of user preferences, it leverages historical data on student grades. Notably, students are aware of which subjects are generally considered more challenging, but not the result of combining them with others in the same semester. Therefore, information about co-enrollment failure rates is not currently available. For a given pair of subjects, it is computed as the probability of failing one of the subjects when taken together.

- D_R Requisites
  Subjects that must be taken in a specific order (i.e., prerequisites) should be positioned with some separation. This is a special case of content-based filtering, which takes into account the subjects that must be taken previously in order to enroll in a specific subject. This relative partial distance is 0 for all pairs of subjects except those that are part of a requisite. In that case, it is 1 for a strong prerequisite and 0.5 for a weak prerequisite (i.e. a recommendation).

- D_O Overlap
  Subjects with a significant overlap in their assessment activity calendars should be positioned further apart. Managing this information is challenging as it is updated every semester and even advisors currently lack access. It is defined as

the percentage of days in the semester where the student must work on two or more activities from both subjects. However, this depends on the number of days the student dedicates to each activity, so it is possible to adjust this relative distance according to this parameter.

Each of these criteria separates each pair of subjects in the N-dimensional space. Therefore, it is necessary to combine all the criteria to obtain the final relative position of the subjects in the N-dimensional space. The resulting distance matrix D is formed as a linear combination of the partial distance matrices D_C, where $w_C \in [0,1]$ represents the weight assigned by the student to criterion C from the preceding list (i.e. Semester, Popularity, Difficulty, Requisites and Overlap), and ε is a small random value introduced to prevent zero distances that would cause subjects to overlap if no other data about a pair of subjects was available:

$$D = \sum_{C} w_C D_C + \varepsilon$$

Subsequently, by applying Sammon's non-metric multidimensional scaling algorithm (Sammon, 1969), points in a 2D space were obtained. These points were then rotated to ensure the degree's capstone project (TFG in Spanish) occupied the rightmost position on the map.

Figure 5.8 - Proof-of-concept of subject placement
Initial subject placement in a two-dimensional space. Subjects are identified by code.

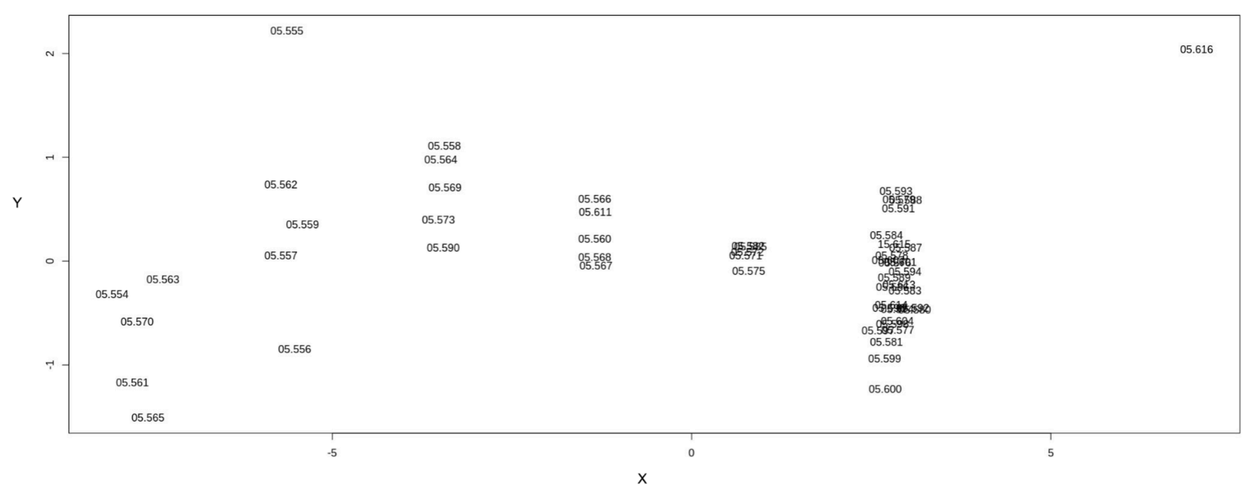


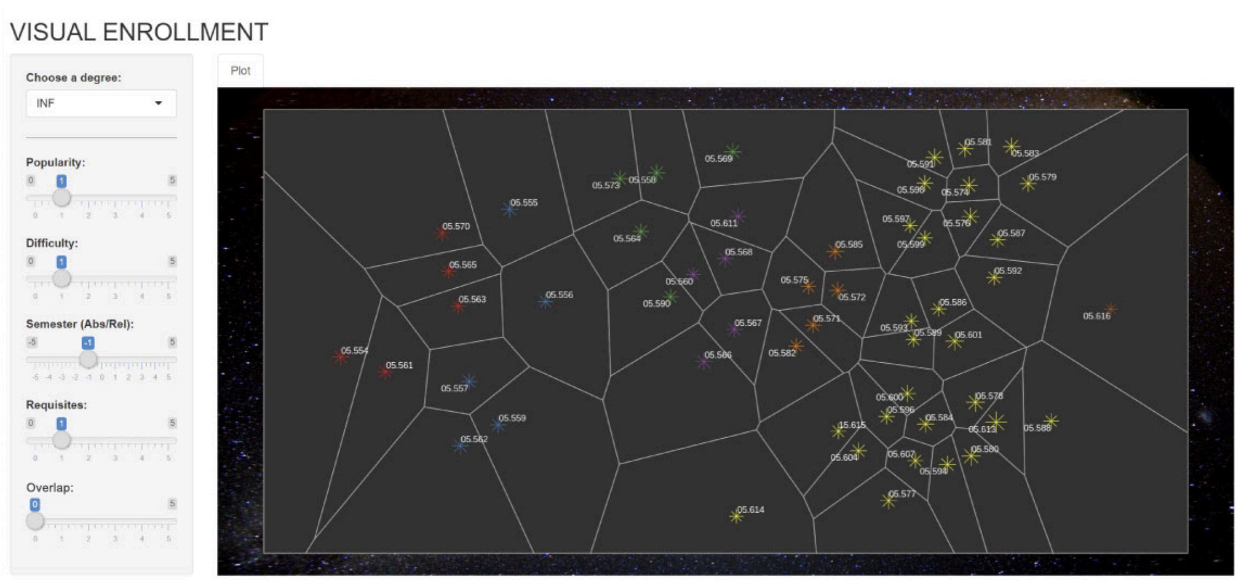
Figure 5.8 exemplifies the raw outcome of this process. In this figure, the subjects are principally arranged horizontally from left to right along the X-axis, according to their absolute semester, thus the arrangement utilizes eight columns (one for each academic semester). It visually represents the curriculum, with subjects mapped across columns. In Figure 4.1 of Chapter 4, which details the study plan's subject types, the sixth column is specifically dedicated to elective subjects, while the seventh column remains empty. This distinction arises because the degree curriculum places all eligible elective subjects starting from the sixth semester, although they can be taken anytime. The degree capstone project (TFG in Spanish) is placed in the eighth column. Vertically on the Y-axis, subjects are positioned based on their difficulty level.

Which means that the difficulty criteria is active and separates subjects that should not be enrolled at the same time. Both axes are determined by the Sammon projection used to calculate the map. The small distances between nearby subjects are caused by the introduced ε. Without such distortion, some subjects with no restrictions or data between them would overlap, reducing map readability.

While this initial attempt represented a significant step, it lacked the characteristics of a true map visualization. The first challenge encountered during the map creation process was subject overlapping. As illustrated in Figure 5.8, this resulted in subjects being visually stacked on top of each other, making it difficult to distinguish them. Several values for ε were systematically tested to ascertain an optimal balance between the accuracy of subject placement and the overall readability of the map. Secondly, to achieve a more refined outcome, the prototype could benefit from a more "map-like" appearance. This was done by strategically spacing the subjects to avoid overcrowding and incorporating the addition of regions and borders within the visualization. Finally, the integration of student record information can be essential to its readability.

Figure 5.9 - Proof-of-concept of a 2D map

One of the first versions of the proof of concept where we explored the idea of a map and the possibility of changing the distances between subjects according to the side menu.



An example of one of the many design iterations conducted is presented in Figure 5.9. This figure showcases the early development of a side menu, allowing students to manipulate the map according to their preferences by means of sliders. Additionally, we included a visual proposal with regional divisions. Subjects were positioned using star icons with color denoting the semester: red for first, blue for second, green for third, purple for fourth, and orange for fifth. Optional subjects were colored yellow, while the degree's capstone project (TFG, denoted by 05.616 in Figure 5.9) was marked in brown.

There is an additional interesting question related to the data used to train the recommendation system. For computing the partial distance matrices that are later combined and projected onto the desired two-dimensional map, the more data available the more robust such matrices will be, as happens in training any machine learning model. As aforementioned, we used all available data to compute the distance matrices for each criteria. Nevertheless, some works have discussed the necessity of using only updated data (Lee et al., 2023), discarding obsolete or even incorrect data, as the context may evolve. In the case of a university degree, this may happen when new subjects are incorporated or removed from the curricula, as well as other changes such as the semester when a subject is supposed to be taken or the necessary prerequisites. Although rare, these changes may occur during a long period of time. Furthermore, subjects also evolve, as their difficulty may change from one semester to the following, or the number of activities used to compute their overlapping, for instance. Therefore, it is important to update the matrices every semester or, at least, every academic year, using only the most recent data (i.e. up to five years). Establishing this threshold was out of the scope of this thesis, but it represents a challenge for any use of the proposed recommendation system in a real scenario.

At this stage of the research, two related work streams diverged: the development and experimentation of the recommendation system, and the creation and testing of the proof of concept. The final design was heavily influenced by the ongoing adjustments to the recommendation system (detailed in the next section).

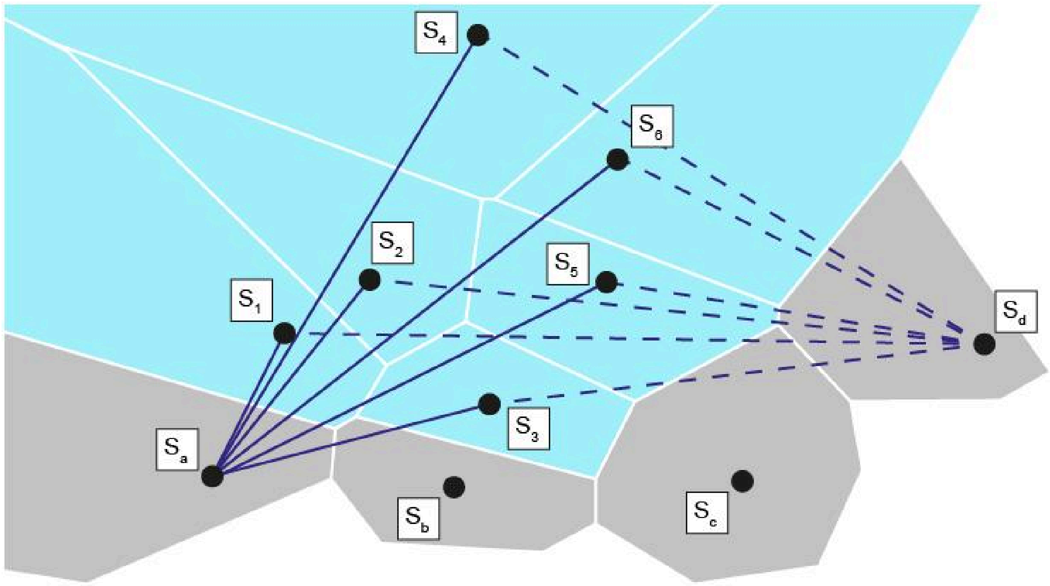
5.3.2 Subject recommendation

The subject map generated by the proposed system is the same for all students (as it uses only historical enrollment data), but they can generate distorted maps based on their preferences by adjusting the weights (w_C) of each criterion by means of the sliders. Once all the subjects have been positioned in the map according to the student's criteria, the recommendation system can select those subjects closer to those already passed (i.e "conquered") by the student. Figure 5.10 shows the process of selecting the subjects to be recommended.

The recommendation system functions by first classifying subjects into three distinct sets. The first set contains all of the subjects that the student decided not to enroll in (such as validated subjects, or discarded subjects). Subjects in this set are not used for computing the recommended subjects. The second set of subjects S_P contains all of the subjects that the student has already passed and therefore they represent the regions of the map that have been already conquered. The third set of subjects S_R contains the rest of the subjects that are potentially part of the enrollment and can be recommended. At this point, for each subject in S_R the average distance to all subjects in S_P is computed, as can be seen in Figure 5.10, where the distances between S_a and S_d are shown with respect to the subjects S_1, to S_6 in S_P. Following this procedure, the six subjects with the lowest average distances are those recommended by the system, which are those six subjects closest to the already "conquered" region S_P.

Figure 5.10 - Subjects distance computation

Distance computed for two potentially recommendable subjects in S_R (namely S_a and S_d, in gray) with respect to the set of passed subjects S_P (in blue). In this case, S_a would be recommended over S_d.



Other aspects related to the enrollment process must be taken into account in any real subject recommendation system. The first of which is the degree organization. Although in most open universities students can enroll in any subject with almost no requirements, they are provided with plenty of information about degree organization and recommended learning paths. Each subject has a recommended semester to be taken (i.e. an absolute semester), taking into account the expected length of the degree (usually eight semesters). In general, data shows that most students follow such institutional recommendations. Therefore, it seems reasonable that such absolute organization has to be included in the map, allowing students to read it from left to right; from the subjects that are supposed to be taken in the first semester to the final subject of the degree. This is forced in the computed map by D_S, which separates subjects that should be taken in different semesters, altogether with its corresponding weight w_C.

Secondly, when students fail a subject and must repeat it, they are not obliged to take it the following semester. Nevertheless, enrollment data shows that most students do it, as they try to take advantage of their effort in the previous semester. Therefore, students with pending subjects should be provided with recommendations tailored to that fact. This can be forced by reducing the computed distance between the pending subjects (which are in S_R) and S_P, multiplying it by a factor $d_R \in [0,1]$. For students with no pending subjects, d_R=1.

Finally, the cold-start problem appears when there is no data for a student or a new subject and the recommendation system is unable to compute any distance between them (Panda & Ray, 2022). In our case, the cold-start problem for new subjects is not particularly important as some data is always available, i.e. the semester when the subject is supposed to be taken, as well as possible subject requirements. It would be a problem, though, for a new degree with no previous enrollment data, as some criteria (popularity and difficulty) would be not available. In that case, the computed map could be degenerated with a lot of overlapping.

However, the cold-start problem could be important when a student has not passed any subject and therefore their S_P set is empty. This means no distances between pending and passed subjects can be computed. In this case, the subjects supposed to be taken in the first semester would be used as the initial recommendation. Considering that the map can be read from left to right (as the map is always rotated so the capstone project or TFG is on the right), that means that the leftmost part of the map would be highlighted as the initial regions to conquer. In other words, the subjects with the lowest x coordinate in the map would be part of the recommendation.

Nevertheless, it is important to take into account that enrollment at UOC in the two first semesters is part of an institutional project for reducing dropout rates called ESPRIA (González et al., 2020), so we decided to use the recommendation systems with students in their third or posterior semester, thus avoiding the cold-start problem. This also eliminates the problem of not having enrollment data for new degrees. Once again, when designing a recommendation system for a scenario as complex as enrollment in an open university, all premises that emerge from such context must be taken into consideration.

5.3.3 Simulations

We carried out some simulations to accurately determine the aforementioned key parameters of the recommendation system, thereby enhancing their predictive performance and user satisfaction. In order to perform the simulations, two datasets were combined: students' needs (described in Chapter 4) and UOC's historical enrollment data (subjects enrolled, passed, failed, and so on). Specifically, we performed an experiment with a simulation of possible enrollment scenarios utilizing real student data. By simulating enrollment decisions based on these factors and comparing the simulations to actual student enrollment data and subsequent grades, we identified enrollment trends. These trends were then incorporated into the design of the future prototype.

We used student data up to the current semester (2020/2) to generate enrollment recommendations for the upcoming semester (2021/1). The distances were calculated by considering the importance given to factors described in Section 5.2.1 as if they were weighted by the student from 1 to 5, but randomly assigned. While the specific factors most important to each student remained unknown at this stage, the system could generate various enrollment combinations (100 per user) based on the factors previously described. Each combination of weights generated a recommendation of six subjects. These recommendations could then be compared to actual student enrollment choices for the 2021/1 semester and their corresponding final grades. It was expected that if a student took a certain factor into account when enrolling (for example, the deadline schedule overlaps), the combinations that favor that factor should get more subjects correct among those recommended.

Table 5.1 - Student's characteristics
Summary of student's characteristics, including demographics and situation within the degree.

Statistic	Mean	St. Dev.	Min	Max
gender (M)	87.9%	-	-	-
age	33.031	8.577	19	67
semester	5.458	2.295	3	11
passed	10.912	7.433	1	41
failed	0.976	1.531	0	13
recognized	4.999	5.362	0	30
recognizable	0.916	2.566	0	23
enrolled	2.810	1.267	1	6
repeated	0.418	0.776	0	5

Table 5.1 presents an overview of the student population used in this study (N=1986). The sample predominantly comprises male students with an average age of thirty-three. Academically, they are mid-career students, typically in their fifth or sixth semester, having successfully completed approximately eleven subjects, almost five recognized subjects and one potentially recognizable. Their enrollment patterns indicate a mix of subject loads, with a mean of two or three subjects enrolled per semester and one repeated subject. This table demonstrates the diversity of the students at the UOC, highlighting the complexity of developing a universally applicable recommendation system. Figure A.6 shows the diversity of the maps computed for real students taking part in the recommendation system evaluation.

Evidently, one significant limitation of this approach was that students did not have access to the proposed recommendation system during the actual enrollment process. Therefore, the true motivations behind their enrollment choices were unknown. It is possible that student enrollment choices were influenced by considerations beyond the scope of the recommendation algorithm. Nevertheless, we aimed to identify factors that hold greater or lesser weight in student decision making by analyzing potential correlations between specific factor configurations and the recommendation system's accuracy in predicting successful enrollments. These are measured by the number of subjects correctly recommended and later passed, amongst other results.

Step 1: Data processing and Distance Matrix Generation

Student data up to the 2020/2 semester was utilized to calculate partial distance matrices for each defined criteria defined in Section 5.3.1. These matrices were subsequently employed to train the recommendation system used in the proof of concept.

Step 2: Simulating Student Interaction with the factors

The simulation allowed students to select any of the proposed factors and weigh their importance on a scale of 1 (least important) to 5 (most important). We generated 100 random combinations of factor weights for each student, simulating various student preferences. As these factor weights changed, the distance-based algorithm dynamically adjusted the distances between subjects. For instance, when the difficulty factor was weighted highly (distance factor = 5), the simulation separated subjects that typically lead to high failure rates when taken together, as if it was one of the factors that the student had decided was important.

Step 3: Generating Recommendations

For each random combination of user-defined weights and parameters, the system generated a set of six recommended subjects. Although assessing the efficacy of a recommendation system is very subjective (Maphosa et al., 2020). In this case, the intentions of the students at the time of making their decision were not known, but the number of guessed subjects could be counted as if they were following some underlying criteria that were related to the system parameters. We conducted a series of experiments to check if the parameters mentioned could be determined by the student's behavior, before further testing the prototype with real students. This is similar to the offline experiments described in Shani and Gunawardana (2011), as offline experiments before proceeding with online evaluation.

While a correct recommendation did not guarantee a student would pass the subjects, it was still important to evaluate the recommendation system's effectiveness. To gain a more comprehensive understanding, the recommendation system's performance could be compared to a random one, where any six subjects could be chosen. To evaluate the recommendation system's effectiveness, the following factors were considered:

- **Recommended Subjects Enrolled:** Out of the one to six subjects a student enrolled in, how many were recommended by the system?
    - **Matched and Passed Recommendations** (rec_{OK})**:** Among the recommended subjects a student enrolled in, how many did the student pass? This reflected a successful recommendation.
    - **Matched and Failed Recommendations** (rec_{KO})**:** Among the recommended subjects a student enrolled in, how many did the student fail? This indicates a potential issue with the recommendation's fit for the student's needs or performance, although it’s a partial success from a recommendation system point of view.
- **Recommended Subjects Not-Enrolled:** Out of the one to six subjects a student enrolled in, how many were not recommended by the system?
    - **Non-Recommended Subjects Passed** (not_{OK})**:** How many subjects did the student pass that were not recommended by the system? While this could be seen as a missed recommendation, it was important to consider the student's reasons for choosing those subjects.

- **Non-Recommended Subjects Failed** (not_{KO})**:** How many subjects did the student fail that were not recommended by the system? This suggested the student might have benefited from the recommendation system's guidance.

For each student enrolling into the first semester of the 2021-2022 subject, we compared their actual enrollment with our recommendation, taking also into account whether the student passed or failed each subject. Then, success rate r was measured as the percentage of recommended subjects that were actually taken by the student, as shown below:

$$r = (rec_{OK} + rec_{KO}) / (rec_{OK} + rec_{KO} + not_{OK} + not_{KO})$$

We also compared the recommendation system to another one that simply picks six subjects randomly from the list of pending subjects. Using the hypergeometric distribution, the probability of guessing one up to K subjects can be computed when six are randomly selected from a set of N subjects, where K is the number of subjects in the set that the student enrolled in. Then, the number of subjects in student's enrollment that were part of our recommendation (i.e. $rec = rec_{OK} + rec_{KO}$) were measured and then compared to the expected number of randomly chosen subjects.

Table 5.2 shows the number of recommended subjects that were part of a student's real enrollment by number of enrolled subjects. The recommendation system was not successful with students who enrolled in only one subject, but it improved significantly the more subjects the students enrolled in (i.e. $r > 0$). Analogously, our recommendation system always outperformed random guessing except for those students enrolled in only one subject. On the other hand, students obtained better results in the subjects that were not recommended by our recommendation system. This behavior indicates that students decide not to advance through the map by conquering neighboring regions, but by making jumps based on their personal interests. Nevertheless, it is worth mentioning that this is the result of a simulation, not of the real use of the system with its other features (detailed in forthcoming sections), so the real behavior and intentions of students are not being captured.

Table 5.2 - Comparison against random guessing
Results of our recommendation system vs random guessing.

Enrolled subjects	N	r = 0	Better than random	rec_{OK} / rec	not_{OK} / not
1	295	51.9%	48.1%	31.6%	41.3%
2	598	32.8%	65.1%	47.9%	59.5%
3	560	20.7%	71.0%	60.8%	70.8%
4	316	12.1%	71.5%	69.5%	76.3%
5	157	11.3%	70.8%	71.1%	83.8%
6	60	7.4%	72.3%	74.6%	82.6%

Based on these results, our recommendation system appears to outperform a random selection, particularly for students enrolling in multiple subjects. Students taking only one subject are most likely to take advantage of the lack of enrollment requirements in an open university, and they are subject-focused rather than degree-focused.

As aforementioned, the recommendation system needs to make accurate predictions but also consider the academic performance of students enrolling into the recommended subjects, which are, to some extent, two unrelated problems. Although the recommendation system was designed to take into account the collective intelligence of students, avoiding strange combinations of subjects, passing or failing a subject depends on a myriad of other factors. Some of which are related to students' personal characteristics, including their context (job and family commitments) in that precise semester. In fact, as one of the basic goals of this thesis, we did not intend to provide students with very accurate recommendations, but with additional information related to degree data that could be used to make better informed decisions. In this research, an exhaustive evaluation of the recommendation system has not been carried out. The reason for this is that the recommendation system is only one of the features of the learning dashboard that contains other elements which must also be evaluated. Furthermore, fine-tuning the recommendation system and its technical aspects is beyond the scope of this thesis. Therefore, we have focused on a more qualitative evaluation, focused on decision making and the impact on the current enrollment procedure.

Regarding the number of correctly recommended subjects, we created two different regression models to estimate the number of recommended subjects that were part of the student's real enrollment (i.e. $rec_{OK}+rec_{KO}$) according to available data. It is important to note that these models were built with the purpose of evaluating the importance of each of the variables available, not to be as accurate as possible. Our goal was to determine the importance of students' characteristics, their situation within the degree and system parameters with respect to the efficiency of the proposed recommendation system. Notice that due to the large size of the data set (1986 x 100), most of the model coefficients will have a very small standard error and, therefore, they will appear as statistically significant. Therefore, only the sign and relative magnitude of the estimates are interesting.

The first model uses only data from students and their situation within the degree, before they make any decision about enrollment. This model would be the simplest one that would perform better than a random recommendation system with the information available just before enrollment. On the other hand, the second model includes information about the number of enrolled subjects, whether the student enrolls into pending subjects (i.e. failed) or not, and the two random parameters d_R and w_s, in order to analyze the relative importance of each parameter. Table 5.3 shows the coefficients and confidence intervals (95%) for both models. Notice that Model 2 is better than Model 1 with respect to both adjusted R^2 and AIC.

Table 5.3 - Comparison of regression models

Regression models (with and without weights and parameters). Note: ∗p<0.1; ∗∗p<0.05; ∗∗∗p<0.01

	Model 1 - No weights or parameters	Model 2 - With weights and parameters
Constant	−0.802∗∗∗ (−0.819, −0.785)	−1.131∗∗∗ (−1.153, −1.109)
gender (M)	−0.027∗∗∗ (−0.037, −0.017)	−0.070∗∗∗ (−0.081, −0.060)
age	0.002∗∗∗ (0.002, 0.003)	0.002∗∗∗ (0.002, 0.003)
semester	−0.009∗∗∗ (−0.011, −0.006)	0.002∗ (0.0001, 0.004)
passed	−0.005∗∗∗ (−0.006, −0.005)	−0.006∗∗∗ (−0.007, −0.006)
failed	0.066∗∗∗ (0.064, 0.068)	−0.083∗∗∗ (−0.087, −0.079)
recognized	−0.004∗∗∗ (−0.005, −0.003)	−0.002∗∗∗ (−0.002, −0.001)
recognizable	−0.027∗∗∗ (−0.028, −0.025)	−0.026∗∗∗ (−0.028, −0.025)
w_S	---	0.130∗∗∗ (0.127, 0.133)
repeats	---	0.381∗∗∗ (0.373, 0.389)
d_R	---	−0.130∗∗∗ (−0.144, −0.115)
repeats:d_R	---	−0.167∗∗∗ (−0.178, −0.156)
Observations	198,600	198,600
Adjusted R2	0.279	0.369
AIC	502,670.7	486,934.4

Table 5.3 presents only the most significant factors revealed in the simulations. This highlights the absence of a single dominant factor among the four described in Section 5.3.1 (Popularity, Difficulty, Requisites, and Overlaps). Notably, the lack of results for the "Requisites" slider is unexpected, as it is the only factor that the students know in advance when they enroll in. Once again, the diversity of student profiles, depending on their situation within the degree and the validated or potentially validated subjects, make it difficult to comply with all of the subject requisites, which should be understood as good recommendations, but are not in fact mandatory. The remaining sliders (Popularity, Difficulty, and Overlaps) were probably not significant because students may lack the necessary information to make selections based on these criteria at this point in the enrollment process.

Nevertheless, valuable enrollment trends, previously hidden within the data, were revealed through these simulations. Notably, a prioritization of re-taking failed subjects was observed, with students aiming for completion as soon as possible following an unsuccessful attempt. This behavior aligns with subsequent confirmation by advisors, as failed subjects are emphasized within their enrollment recommendations (Section 5.4.1). Additionally, simulations revealed that student subject selection generally aligns with the recommended semester structure. In other words, the order of subjects within a semester emerged as a significant factor influencing student choices. Based on this finding, the semester order slider was relocated to a separate tab designated for administrative use. Furthermore, the system was configured to prioritize these factors by default, as shown in Table 5.4.

Table 5.4 - Outcomes of the simulations
Summary of changes for prototype development derived from simulations.

Design Feature	Changes
Recommendation system	Prioritize subjects not passed when recommending
	Users can choose which subjects to include or exclude from recommendations.
Sliders	Remove the slider with the “Semester” factor from the user view

Simulations also suggested a tendency among students to avoid enrolling in subjects they may recognize from previous studies. This highlights the importance of offering a functionality that allows users to exclude such subjects from their selections. However, implementing this functionality presents a significant challenge due to data collection issues. For instance, many UOC students come from diverse academic backgrounds, often transferring from other degrees or higher education institutions. In some cases, students begin their studies without having their previous subjects officially validated, although they may have a general understanding of which subjects will be recognized. Official confirmation is required before these validated subjects can be added to their UOC academic record. Moreover, many students postpone this process until the very end of their degree program. Therefore, we decided to provide a manual mechanism to specify those subjects that a student does not want to be part of the recommendation. Following the interpretation of these results, they were integrated into the evolving proof of concept. The next section provides a step-by-step breakdown of its development.

5.3 Proof of concept

While we addressed the primary technical challenges, we conducted design explorations for the proof of concept concurrently. Detailed documentation of these design tests can be found in Annex A.2. As illustrated in Figure 5.8 and in other projects described in Chapter 2 (see Ma et al., 2021, for instance), simply positioning subjects at specific distances did not guarantee a readily comprehensible visualization. A transformation of this positioning was deemed necessary. We achieved this through the implementation of the Voronoi diagram (See Figures 5.9 and 5.11 as early examples of its implementation), which was used to create adjacent regions around points (i.e. subjects). A Voronoi diagram separates a 2D space into convex regions generated from a collection of points representing the centers of each region. In this case, each subject has been assigned to a region. This process transformed the subjects into conquerable regions for the user. Subjects positioned closest to those previously completed have become the most likely candidates for further progress, as in Risk and Catan maps presented in Figure 5.5.

5.3.1 Visualizing the study plan

As can be seen in Figure 5.11, the distance between subjects centers in this visualization reflected the weight assigned to factors previously explained: difficulty (subjects historically failed more often when taken together), popularity (subjects frequently enrolled in together), prerequisites (subjects that must be taken before others), deadline schedule overlaps (subjects that have similar deadline dates), study plan sequence, and failed subjects. The recommendation system would recommend six subjects that are close to each other. Recommending subjects was in essence a process of "filling out" the map, taking into account the subjects already passed. In Figure 5.11 we prioritized semester organization within the map visualization. While we incorporated other factors (difficulty, requisites, and overlaps), we assigned them lesser weights. Note that an earlier iteration of the proof-of-concept displayed phases aligned with the student's semesters (My marks) within the map.

Furthermore, we generated a personalized two-dimensional map for each student, reflecting past enrollment data and academic performance (Figure 5.12). In prioritization of interpretability over absolute accuracy (McNee et al., 2006), our focus was on representing *typical* students and *reasonable* enrollment patterns. To achieve this, Shneiderman's mantra – *"Overview first > Zoom and filter > Details on demand"* – was adopted through the implementation of an interactive learning dashboard (Schwendimann et al., 2017). Figure 5.12 also shows basic subject codes highlighted through the use of transparency for non-basic subjects. Subjects not yet passed were initially colored red, while passed subjects were colored gray. Available subjects were presented in light blue.

Figure 5.11 - Example of degree map with sliders

Subject map with Voronoi diagram applied. Users can rate different factors according to their importance, modifying the distances between subject centers.

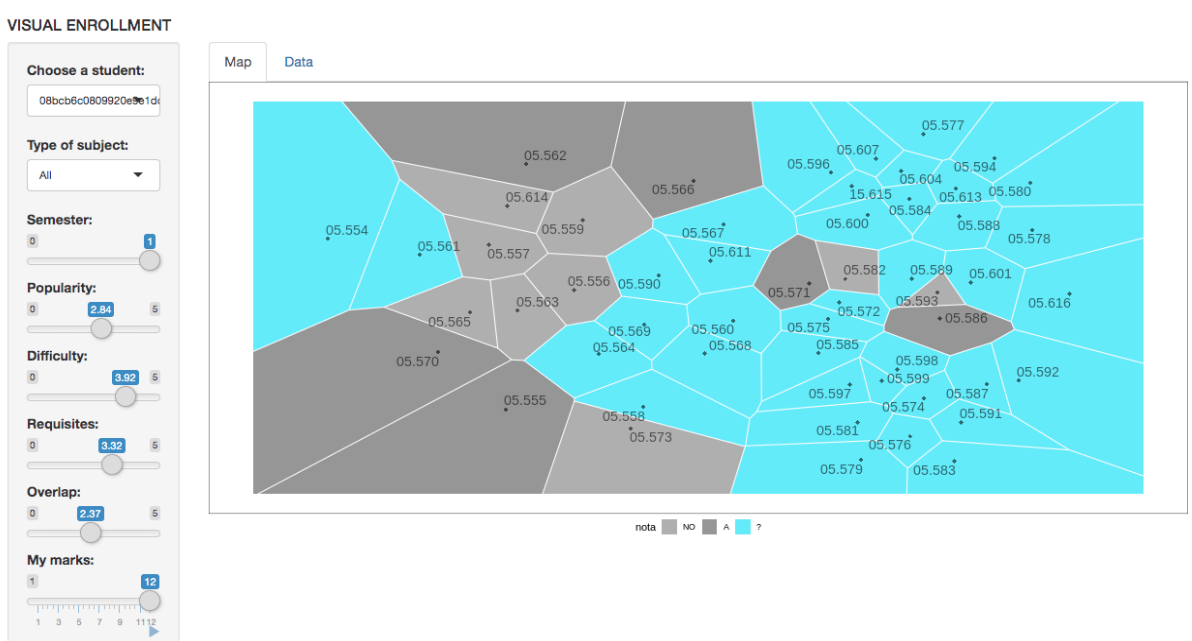
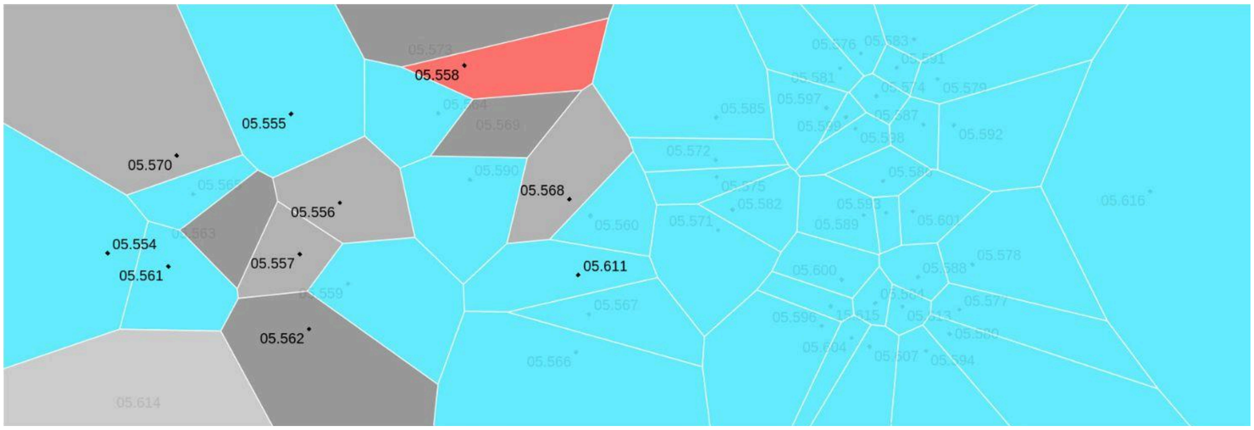


Figure 5.12 - Example of student academic record

A student academic record was selected from the database and a personalized two-dimensional map was generated.



Following the successful positioning of subjects based on student preferences and the creation of the map, we tried to enhance the design of the proof of concept interface and its usability. Several early design tests were carried out to achieve this. As illustrated in Figure 5.13, initial efforts focused on emphasizing the "conquest" concept through the incorporation of icons representing various subject types: basic, mandatory, elective, etc. However, this approach did not demonstrably improve the readability of the computer science degree map.

Figure 5.13 - Example of different visual attributes

A design test with icons for different types of subjects.

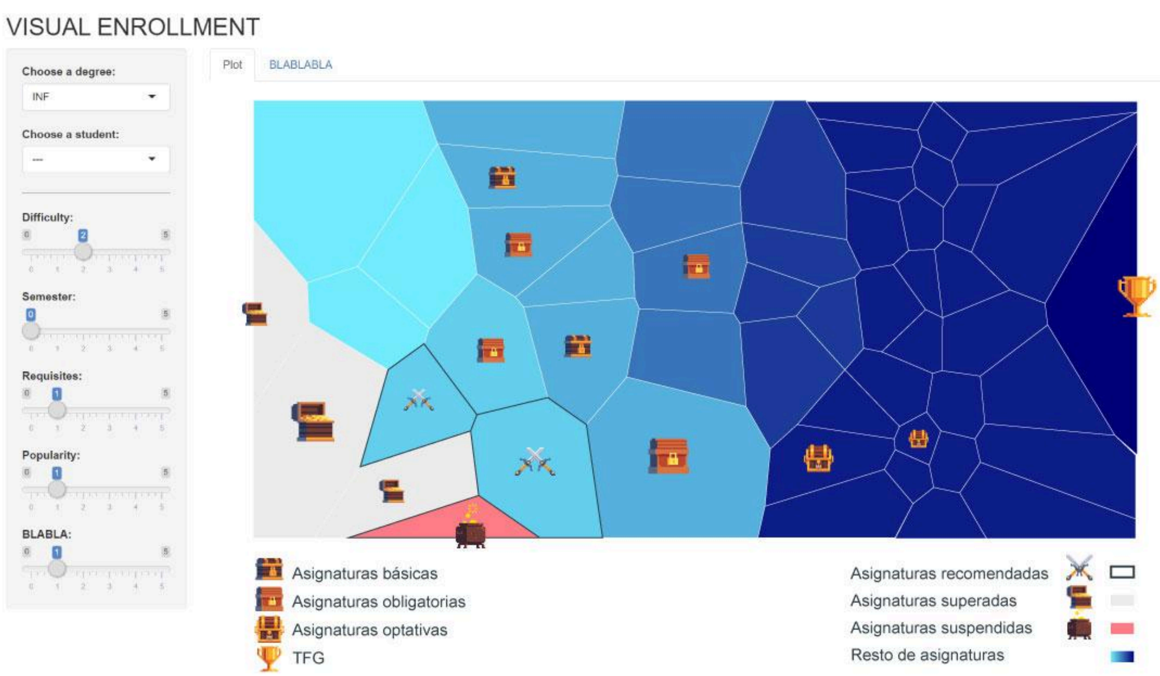
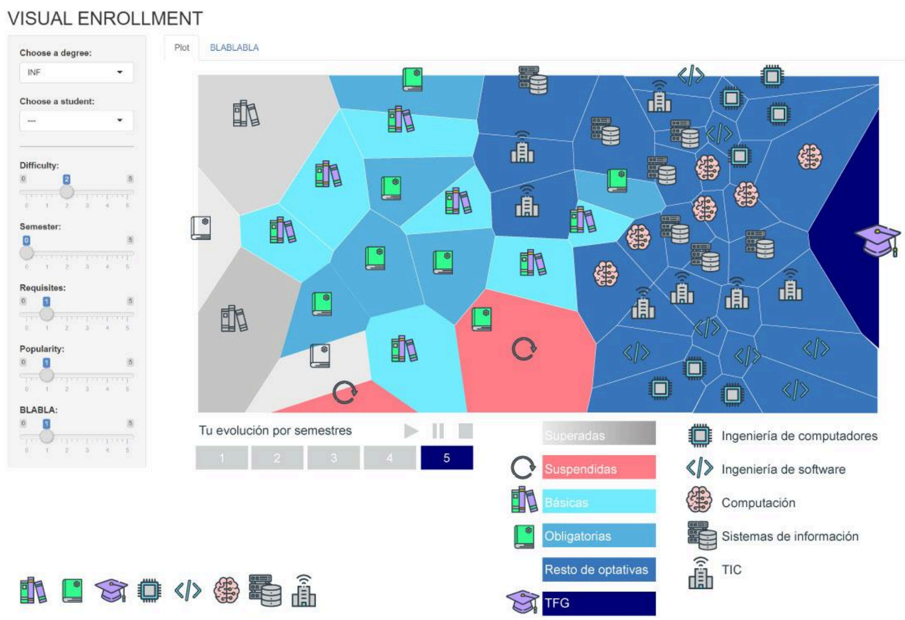


Figure 5.14 - Example of map with icons
A test with all of the icons placed on the map.

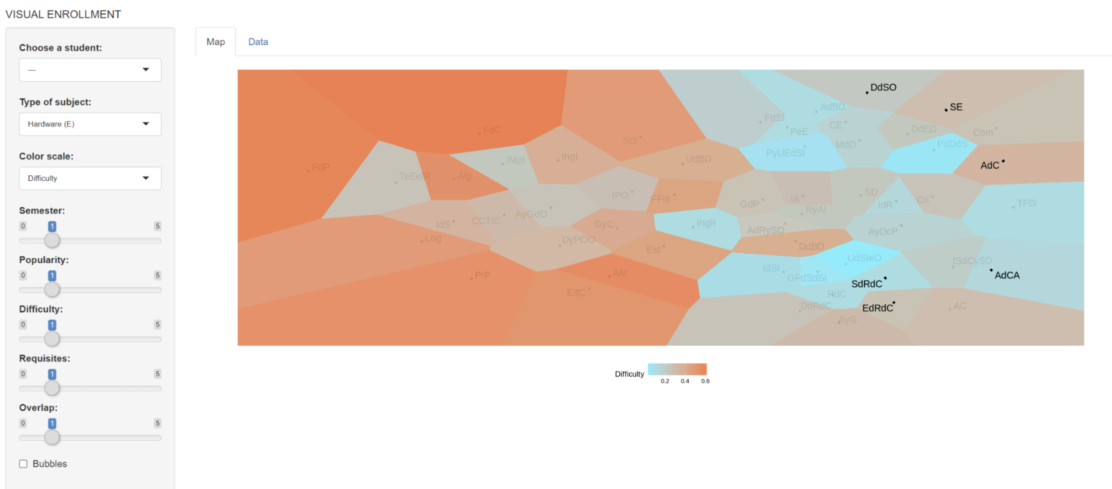


A variety of icon styles were explored, as exemplified in Figure 5.14. However, these iterations consistently resulted in maps overloaded with information. Consequently, we preferred to prioritize simplicity by incorporating subject initials directly into the visualization (see Figure 5.15). Furthermore, we conducted design tests utilizing different color schemes (Figure 5.16). While these initial attempts were ultimately abandoned, valuable insights were gleaned. Specifically, certain color combinations tested during this phase would later be reevaluated with real users, yielding positive user experience improvements.

Figure 5.15 - Example of map with colors and icons
Color and icon design test. The gray color for pending subjects was used in later stages of the development process.

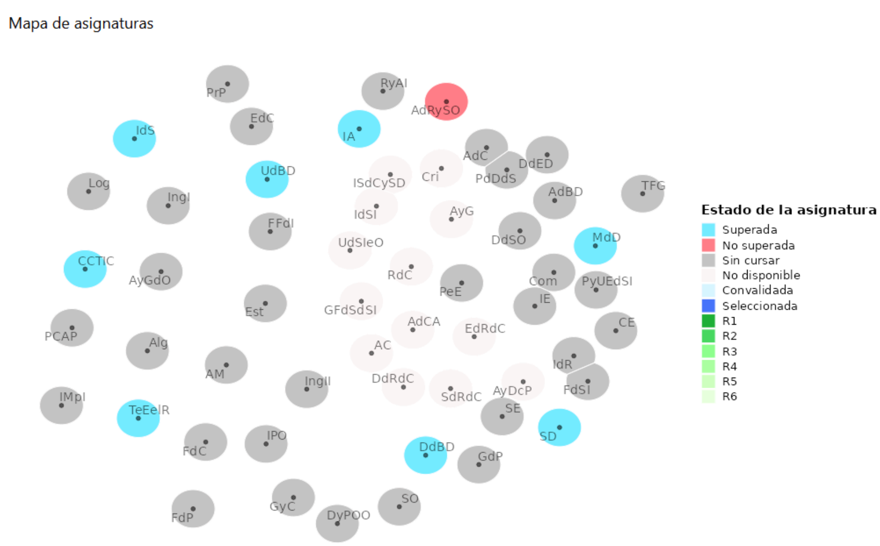
An additional approach explored during this phase involved the creation of color gradations based on user-selected factors. Figure 5.16 exemplifies this concept, where subjects were colored according to their difficulty, with orange representing the most challenging subjects and blue representing the least challenging ones.

Figure 5.16 - Example of map with subject difficulty color scale
Color test showing the difficulty of the subjects and the subject initials.



While the map metaphor implies subject regions of varying sizes, we conducted an experiment to test the implications of assigning equal sizes to all subjects (as seen in Figure 5.17 and Figure A.5). However, this approach was discarded as it disrupted the underlying map metaphor, undermining the concept of 'conquering' subjects within the student's academic journey.

Figure 5.17 - Example of map without Voronoi regions
Visual representation of the subjects within the Computer Science degree program using bubbles. The distance algorithm between subjects has been maintained, but the Voronoi graph has been changed to a bubble graph.

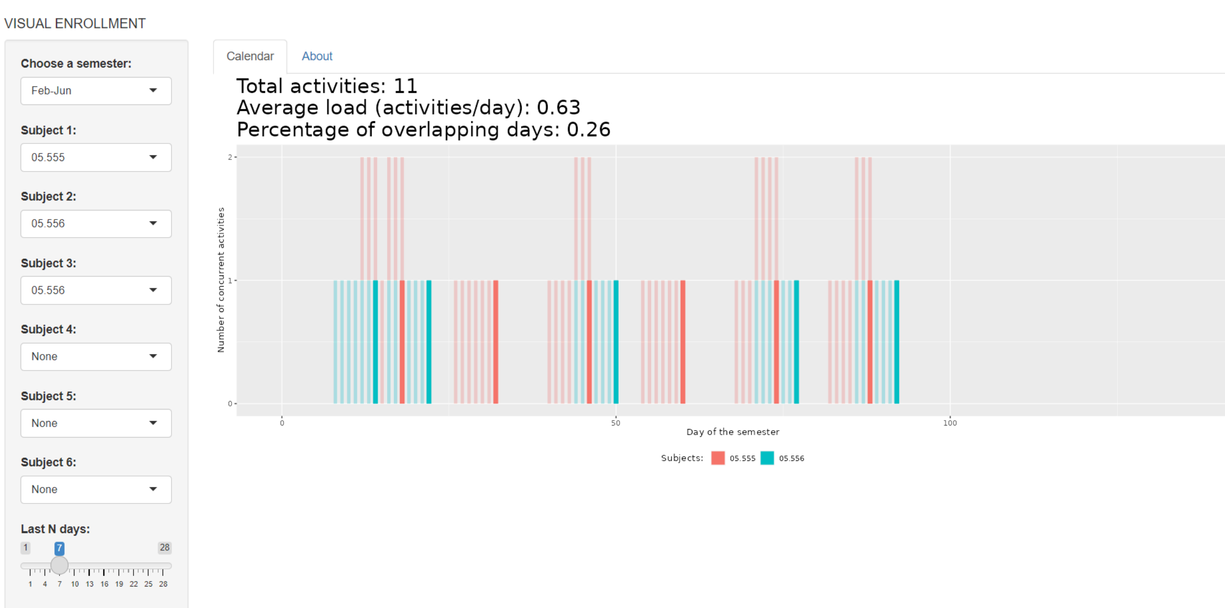


As can be seen in these early attempts, the visualization aimed to empower students by providing a visual representation of their study plan, highlighting their current location and missing elements ("I'm here, and this is what I'm missing"). The final prototype would also incorporate an additional layer of information: the six subjects recommended by the system taking into account the previously described distances.

While this evolving proof of concept was a valuable first step, it laid the foundation for a more comprehensive prototype that included additional functionalities, such as a calendar view within a more complete learning dashboard. Figure 5.18 presents an early proof of concept for this secondary visualization. Upon selecting different subjects, a bar graph was automatically generated to display the accumulated deadline load. Additionally, we included a new slider indicating the desired timeframe for considering upcoming subject deliveries (last N days). This feature is directly linked to the concept of Overlap introduced in Section 5.3.1 (D_O). As this data was unavailable during this phase of the project, it will be gathered through user feedback during the prototype validation. This second visualization could be particularly useful when a student had one or two clear subject choices but doubts about a second or third one. In these scenarios, the recommendation system would suggest six subjects in a certain order. While the recommendation system would prioritize six subjects in a ranked order to aid the student's decision-making process, other factors might ultimately influence their choices. This second visualization, addressing the established importance of time as a decision factor (Chapter 4), seemed indispensable for the future prototype.

Figure 5.18 - Example of calendar visualization

Early calendar visualization proof of concept. Users can select their semester and subjects by code to view the deliveries. In addition, they have a slider to determine the number of days until deadline (Last N days)



As emphasized in the introduction, a user-centered design approach is based on the incorporation of user feedback. Following the development of these proof of concepts, several informal student interviews were conducted to evaluate and refine them. This process allowed for the integration of the resulting conclusions into the final learning dashboard design.

5.3.2 Student interviews

Prior to finalizing the prototype's development, we conducted user feedback sessions with real students to assess the map and calendar proof of concepts. As discussed in previous sections, this aligned with a user-centered design approach. The purpose of these interviews was to evaluate the various functionalities and identify the best features developed thus far. Specifically, the map and calendar visualizations were presented for user feedback during the interviews. The complete protocol for these informal interviews is available in Annex A.3.

We selected four students who expressed interest in further inquiry through the Chapter 4 questionnaire and desired to participate in the interviews. The interview protocol involved conducting individual video calls with each student. During these calls, the map interface (Figure 5.19) and the subject calendar (Figure 5.18) were used by the student and presented on-screen. Both visualizations required the user to manually load data, as the interviews were conducted using the proof of concept, not the real prototype. The user interviews aimed to assess several aspects of the map visualization. First, we evaluated the general comprehension of the tool at a glance. Additionally, we examined some basic tasks such as selecting subject types and applying color filters based on various factors (Figure 5.19). Furthermore, we assessed user understanding of the sliders and their impact on map distortion as well as the compression of the academic record before and after student data loading (Figures 5.19 and 5.20, respectively). Finally, we designed the interviews to investigate whether the calendar visualization effectively conveyed workload information to the students. Figure 5.18 illustrates the calendar interface presented during the interviews.

Figure 5.19 - First map tested with students

Map visualization at the time of starting the interviews. In this case, student's academic record was not uploaded.

As expected, the informal interviews yielded a mix of positive and negative feedback. In terms of general at a glance comprehension, two students grasped the concept of a map but struggled to pinpoint its specific purpose. In fact, these students commented on finding the map concept unusual compared to their familiarity with list-based visualizations. The remaining two participants successfully grasped the "subject map" concept. While all participants demonstrated a basic understanding of the factor functionalities, they did not fully comprehend the resulting changes in subject distribution within the map. Conversely, basic tasks such as subject type selection and difficulty coloring (Figure 5.16) were successfully comprehended by all participants. Regarding the understanding of the sliders, no student considered that forcing the semester slider improved the visualization. Initially, students misinterpreted the size of larger subjects as indicative of higher difficulty (when this was not the intended representation). However, following an explanation of the distance concept, they were able to correctly identify the most challenging subjects.

Following the upload of individual student records (Figure 5.20), three students successfully interpreted the visualization of passed subjects. However, one student mistakenly identified the blue-colored subjects as passed subjects. This observation played a crucial role in prompting a color palette revision within the later development of the prototype. Unanimously, students correctly interpreted the red-colored subjects as not passed. Furthermore, a significant success emerged from the user interviews: students intuitively identified the subjects positioned closest to their passed subjects as the most relevant choices for upcoming semesters. This confirmed the effectiveness of the visual representation of "filling in the gaps".

Figure 5.20 - Map including the academic record

Map visualization when uploading the academic record of one of the students. The subjects passed appear in gray, the subjects not passed in red and the subjects that can be enrolled in blue.

Although the initial presentation of the academic record as a map might have surprised students, they ultimately adapted to the visualization. Recognition of their taken subjects when uploading individual records played a significant role in facilitating comprehension. Therefore, the student record visualization served as an affordance (Hartson, 2003), helping users understand the "degree as a map" concept. The user interviews yielded positive feedback regarding the map visualization. Students particularly appreciated the ability to view all subjects at once and to have the possibility to change the sliders based on their preferences. The chosen factors were also perceived as relevant. The overall impression of the map was one of agility, practicality, and usefulness. Students expressed satisfaction with the ability to see their academic progress at a glance and identify the remaining subjects to complete their degree.

The user interviews also identified areas for improvement. The map interface was perceived as somewhat confusing by some students. Suggestions for improvement included color palette and map legend revisions, along with the possibility of changing the abbreviation of subject names. Additionally, students expressed a desire to view subjects specific to particular semesters (as some subjects have semester restrictions). A request for clearer visualization of subject dependencies and the application of the various factors were also made. Finally, regarding validation functionalities, students suggested the implementation of a feature to mark validated or potentially validated subjects, with such subjects appearing in a distinct color.

The calendar visualization proved successful, as students readily identified subject deliveries. However, the concept of "days until deadline" presented a comprehension challenge. Despite this obstacle, students were able to grasp the workload information and make informed decisions regarding subject selection, taking into account the workload. The visualization of deadline overlaps was particularly well-received, with some students even mentioning they have already developed similar tools using Excel or Trello. Furthermore, all four students expressed strong interest in the potential implementation of a learning dashboard that incorporated both the map and calendar visualizations.

The user assessments resulted in a series of changes and improvements, detailed in Table 5.5, which we incorporated into the development of the prototype and subsequent iterations. The map visualization received an overhaul with a prominent title, legend, pre-loaded student records, full subject names, and upcoming semester information. Additionally, we refined the slider explanations and removed the semester slider due to redundancy with the map view. The calendar was identified as the most valuable feature so we enhanced it with some legends in the visualization, a days until deadline selector and other indicators. Finally, we improved the overall dashboard experience by combining the map and calendar views into a single interface along with the ability to download the deadline calendar for the chosen subjects.

Table 5.5 - Changes proposed for the prototype
Summary of changes for prototype development.

Design Feature	Changes
Map visualization	Include an H1: Subject Map
	Improve the design of the map legends
	Have the student's academic record already loaded into the map
	Add the full names of the subjects
	Visualize subjects that will not be offered the following semester
	Change passed subjects to blue and not taken subjects to gray
Sliders	Improve understanding of the sliders by explaining the concept of distance under each of the factors
	Remove the slider with the “Semester” factor from the user view
Calendar	Include weeks (or months) of the semester and number of activities to delimit the X and Y axis
	Leave number of days until deadline at 0, so the user visualizes first the deadline dates and then adds the workload
	Include the total number of activities
Learning dashboard	Show both visualizations in the same dashboard
	Subjects shown in the calendar can be selected from the map
	The deadline calendar for the selected subjects can be downloaded

5.4 Learning dashboard prototype

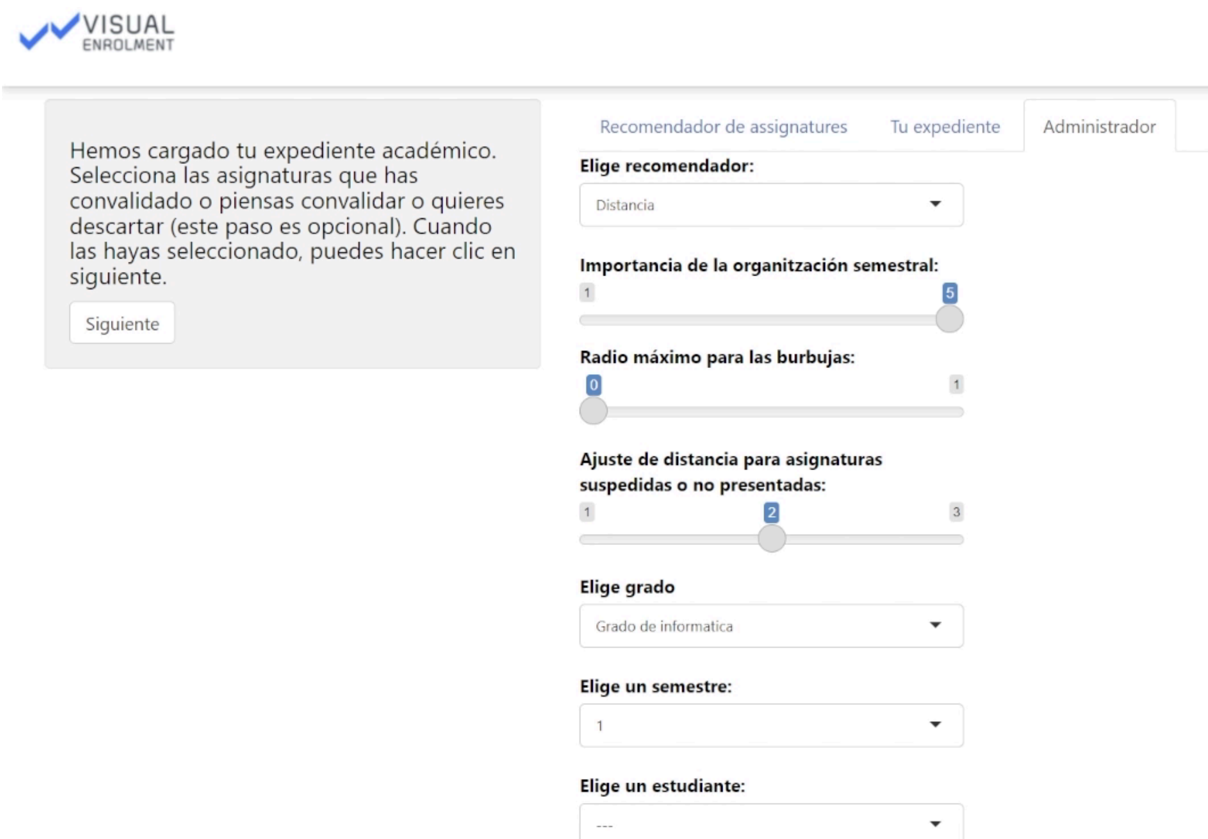
Following the selection of the map concept as the design's core principle, we developed a recommendation system and a proof of concept. After that, we tested these concepts through student interviews and simulations. Informed by the feedback received, we created a refined prototype for the learning dashboard and integrated the recommendation system. The focus throughout the process remained on creating a user-friendly and highly interactive prototype. In addition to the modifications addressed in prior sections, we implemented the following changes:

- Some interface issues were fixed
- Data loading, intermediate calculations, and interactive visualization were separated to enhance performance
- A functionality was created to select subjects and not include them in the recommendation (for example, the user was able to discard validated subjects)
- The recommendation system was integrated into the map display
- The calendar proof of concept was incorporated as an additional functionality

- A multi-step process was integrated to facilitate navigation
- A help layer was added to enhance user comprehension of all tools

Beyond the learning dashboard display tab, the tool offers additional tabs: one for viewing academic record data and another for administrative functions. This administrator tab allows adjustments to certain parameters, such as uploading student data and modifying the default weighting of subject order in the visualization (Figure 5.21).

Figure 5.21 - System configuration interface
Administrator tab that incorporates some extra options such as selecting a recommendation system, changes in the visualization system, the possibility of selecting other degrees, semesters or student academic records.



Furthermore, in order to improve user navigation, we implemented a multi-step process (as illustrated in Figures 5.22 to 5.26). Figure 5.22 depicting the initial step of the student recommendation process, where the student's record is uploaded. This version of the prototype differentiates passed subjects (marked in blue), failed subjects (marked in red), subjects available for enrollment (marked in gray) and subjects that are not offered for the next semester (marked in light gray). In this first step, users were required to mark subjects they wish to exclude from the final recommendation (light blue). These subjects will normally be validated or pending validation subjects. Given that the final subject recommendation will disregard these subjects, this initial step assumes particular importance.

Figure 5.22 - Example of subject exclusion

Prototype interface for subject exclusion in recommendation (Step 1). Users can select the subjects they do not wish to enroll in and these will be marked in light blue.

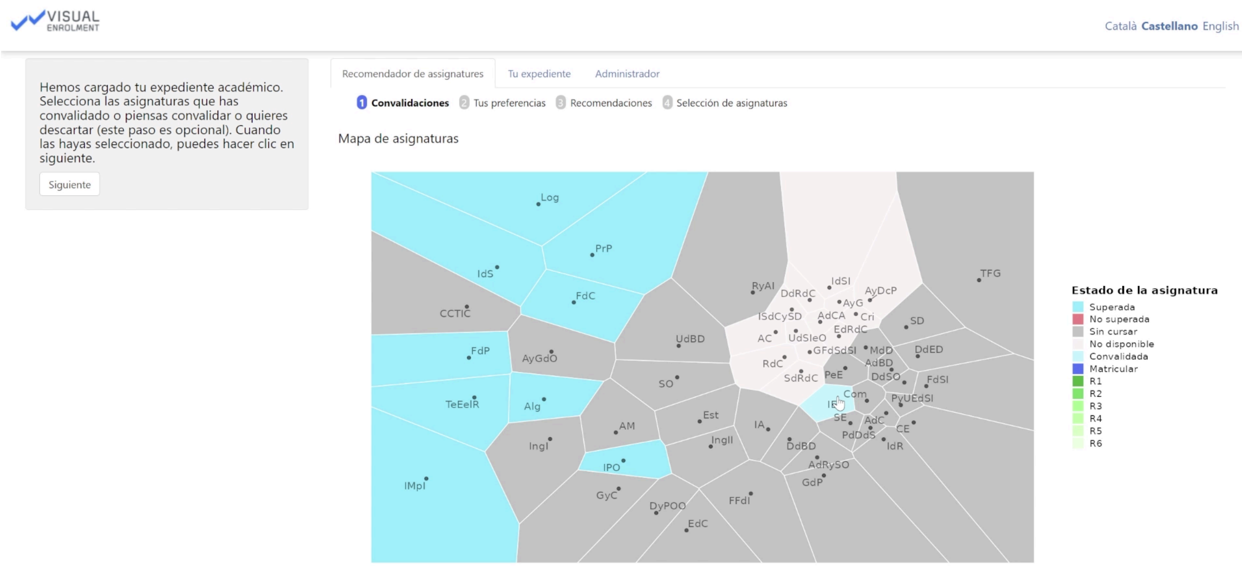
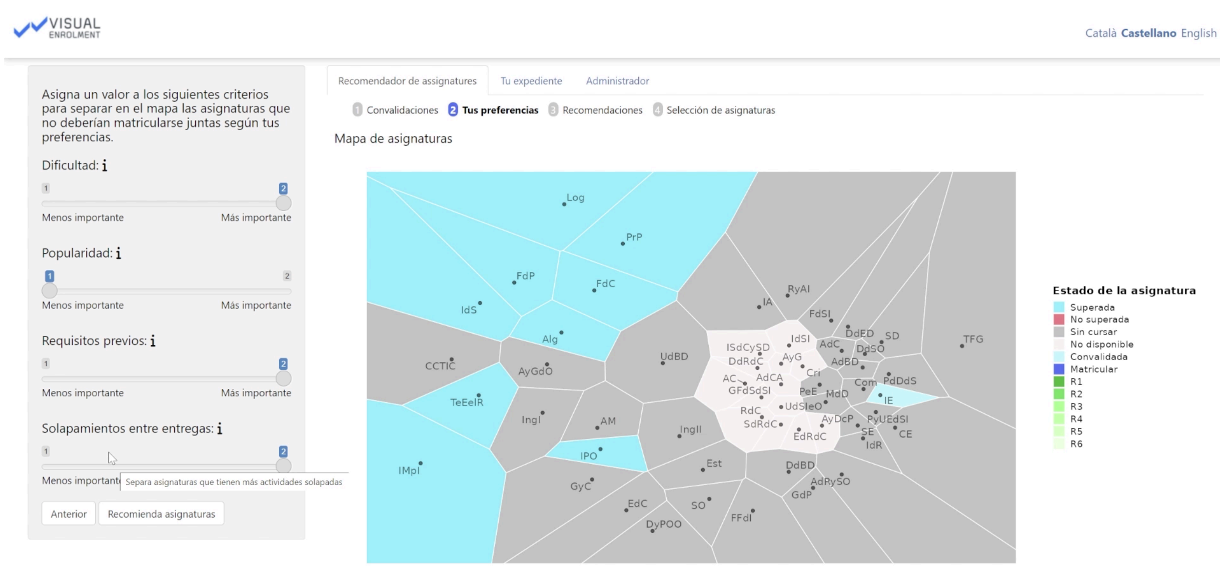


Figure 5.23 - Example of criteria weighting

Prototype interface for criteria weighting (Step 2). Users can rate the following factors according to their importance: Difficulty, popularity, prerequisites, and overlaps. Subject centers will be separated taking into account the selected values.

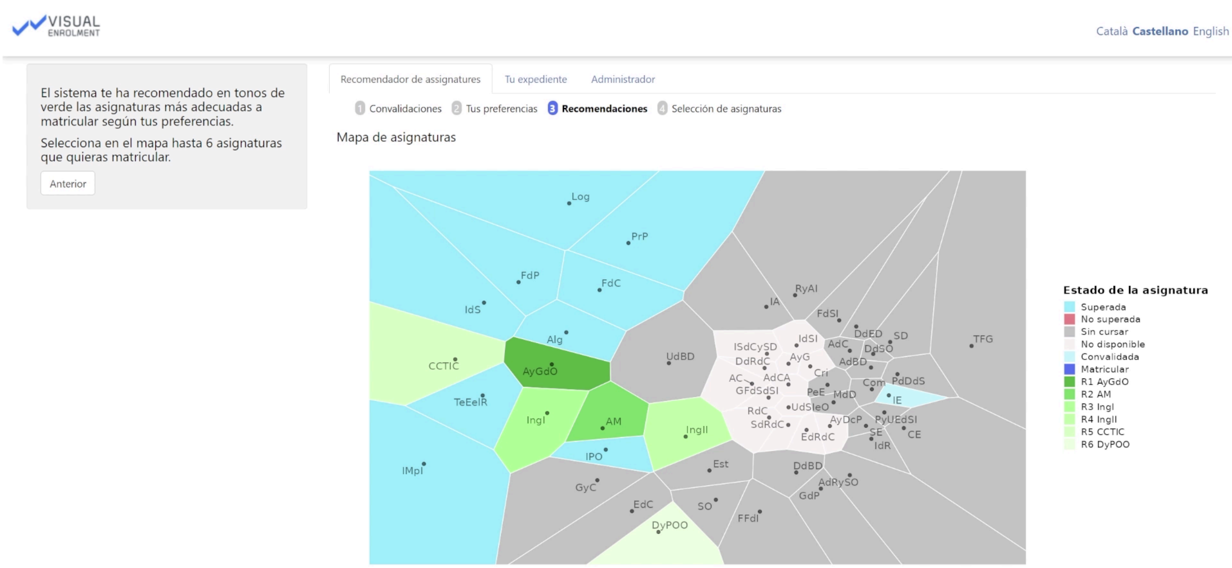


In the second step, students personalize the recommendation process by assigning weights (from 1 to 5) to various criteria: Difficulty, Popularity, Prerequisites, and Overlaps between deadlines. These weight assignments dynamically modify the map to reflect their individual preferences. Consequently, the map separates subjects that shouldn't be taken together based on the chosen weights (Figure 5.23).

Upon marking their validated subjects and preferences, students can click on the "Recommend subjects" button. As illustrated in Figure 5.24, the system automatically highlights the six most suitable subjects for the next enrollment period using a green color. It is important to recall, as discussed in Section 5.3, that these recommendations prioritize subjects closest to those previously completed by the student, always taking into account the importance given to the different factors.

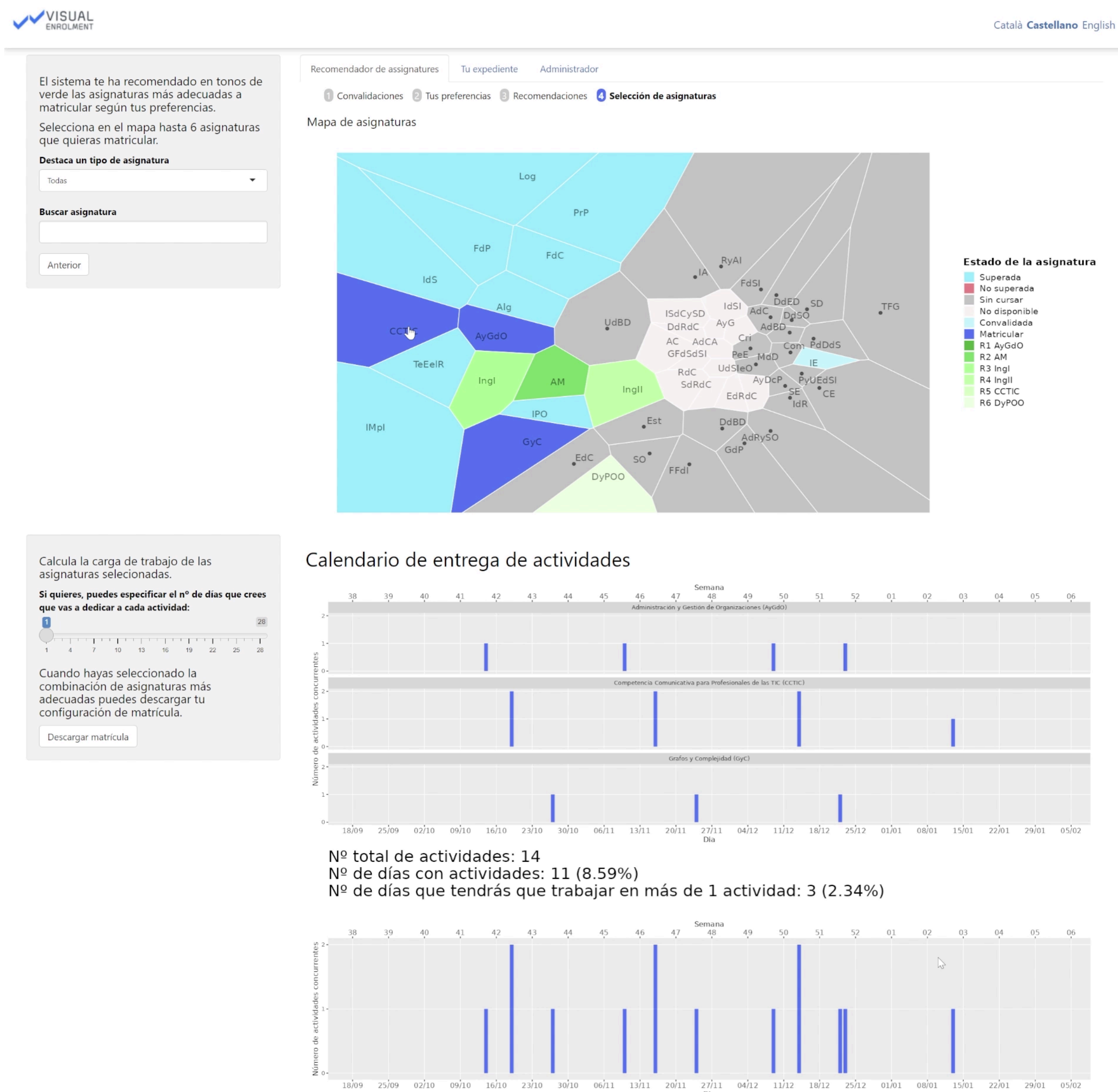
Figure 5.24 - Example of recommendation

Prototype interface for visualizing recommendations (Step 3). The recommended subjects are marked in different shades of green and can be selected (or not) by the user.



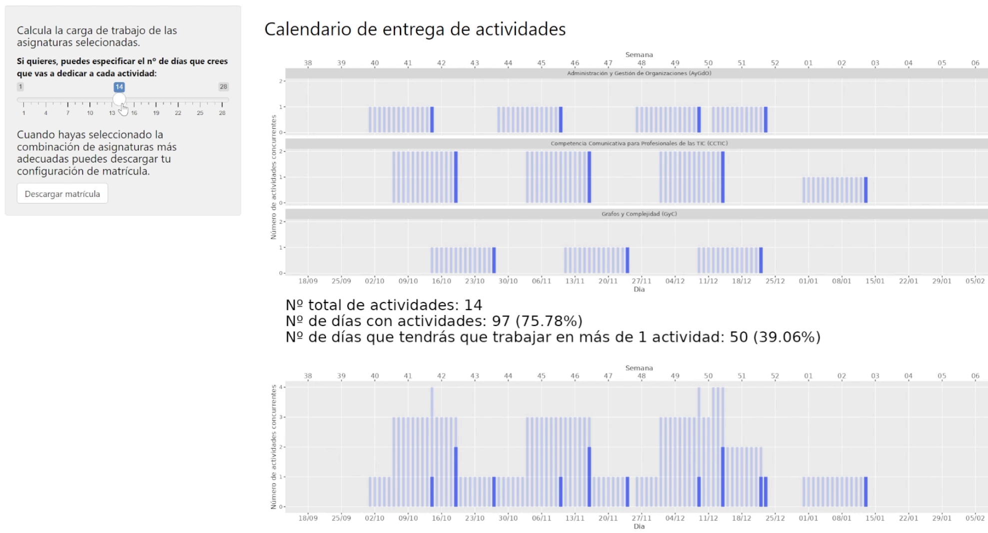
During this step, the user could also highlight subjects by type (basic, compulsory, and optional according to their itinerary) and search for a specific subject. Once the recommendation is made, the user can select the desired subject, which will then be marked in dark blue. Additionally, a secondary visualization displaying the deadline schedule will appear (see Figure 5.25). The user has the flexibility to return to the map view, deselect chosen subjects, and select others if the calendar does not meet their needs.

Figure 5.25 - Example of map and calendar visualization
Prototype interface for subject selection and calendar view (Step 4). Subjects selected by the user are marked in dark blue. At the same time, a second visualization with the deadline calendar appears at the bottom of the learning dashboard. When selecting and deselecting subjects, the second visualization also changes, adding a layer of interactivity.



The deadline calendar displays deadline dates in dark blue. Additionally, users can assign a desired lead time (number of days before the deadline). This assigned lead time is then used to visualize the workload for each subject, with a separate row for the total workload (Figure 5.26).

Figure 5.26 - Example of calendar visualization
Workload visualization (Step 5). Users can assign a number of days leading up to the deadline to check for overlaps between subjects and their workload.



5.4.1 Advisors interviews

While a prototype had already been developed, further testing with real users was still necessary. Prior to student involvement, we determined that initial testing should be conducted with advisors for the following reasons: Firstly, research by Akhter (2012) suggests a close correlation between advisor performance and the enrollment rate of distance students in specific areas. Secondly, several studies highlight the positive impact of a strong advisor-student relationship on student satisfaction, success, and retention (Alexitch, 2002; Ellis, 2014; Habley & Morales, 1998; Yarbrough, 2002). Building upon the finding that advisors were perceived as a less valuable source of information than the institutional website, the proposed learning dashboard's potential extended beyond only student use. We envisioned the dashboard as a dialogue space for both students and advisors that could be a valuable avenue for further research. Therefore, this research explored how the dashboard could be designed to facilitate communication and enhance support during enrollment for better decision making.

We conducted this interview in order to gain insights into the usability and effectiveness of the learning dashboard from an academic advisor's standpoint. We explored several key factors including overall user experience, perceptions of the learning dashboard design, recommendation process procedures, and potential changes in the advisor's decision-making process resulting from the use of the tool. Additionally, the interview presented the opportunity to gain a deeper understanding of the existing advisor recommendation process and any shortcomings identified by advisors regarding their current informational tools.

We created a multi-step evaluation process. Firstly, we selected a single beta advisor to test for potential errors within the protocol. Subsequently, we choose eight advisors to participate in the main evaluation. A standardized protocol was then established. This protocol involved sending each advisor four student records via email, along with a link to a questionnaire in Google Forms and an explanatory video demonstrating the tool's functionalities. Finally, interviews were conducted with each advisor. All protocol materials can be found in Annex A.5. The interview recordings were then transcribed and coded for thematic analysis.

To facilitate the research, we selected an advisor to serve as a beta user. After that, we sent this advisor a file via email containing data from a Computer Science degree student (see example in Annex A.4.1). Additionally, a short questionnaire was included for the advisor to complete regarding the following aspects:

- How many subjects would you recommend enrolling in and why?
- What subjects would you recommend and why?
- How do you organize and what information do you take into account to recommend subjects to your students?

The beta advisor recommended three subjects to the student in this scenario. One recommendation was a basic subject that the student enrolled in but did not take. Another was a failed subject related to one the student had already passed, potentially leveraging existing knowledge for success. The final recommendation was another previously failed subject. All three subjects belonged to the first year of the degree program. In essence, the advisor's suggestion for this particular student file was to re-enroll in the three previously failed first-year subjects (ideally before progressing to higher-level subjects with potential prerequisites).

Regarding the recommendation process, the advisor follows the process described in Section 4.1. If the student and the advisor proposals differ, the advisor starts a discussion with the student to understand their rationale. For example, some students might express reluctance to re-enroll in a recently failed subject. In contrast, the advisor generally recommends re-enrolling in failed subjects as soon as possible. This aligns with findings from the recommendation system simulations. Students may also choose to enroll in multiple subjects from a single itinerary simultaneously, even when prerequisites exist between them. This decision is often driven by a desire to condense their studies, as some subjects are offered in just one of the semesters. Therefore, if they don't take the subjects together, they might face a year-long wait before re-enrollment is possible. This can be a significant obstacle for students aiming to complete their studies within a specific timeframe.

Significant discrepancies between the advisor's and student's enrollment proposals can arise for a number of reasons. One possibility is that the student, having more flexibility due to not working full-time, might propose enrolling in a larger number of subjects. Additionally, the student's record may contain validated or pending validation subjects that haven't been updated in the system yet, making them invisible to the advisor.

Actually, in order to create an appropriate counter-proposal, the advisor must consult several information sources:

- Student's admission pathway to the degree program.
- Student's enrollment intentions: The advisor typically inquires about the desired number and specific subjects the student wants to enroll in.
- Student's academic record: A thorough review is required, including passed/validated subjects, failed subjects, the student's itinerary, and their average semester enrollment load.
- After gathering all of this information, the advisor consults the official diagram of enrollment recommendations for the degree (see Figure 4.4).

Therefore, to formulate a counter-proposal for enrollment, the advisor must first consult at least four key sources of information. This is the standard procedure for the beta advisor but similar information gathering practices are followed by the other 8 advisors consulted in this research.

After collecting the requested information, an interview using the UOC's Google Meets system was conducted. During the interview, a link to the learning dashboard prototype was shared with the beta advisor. A series of questions were then asked to gain insights into the participant's understanding of the visualizations and recommended system:

- Explain the information displayed in the graph. Could you describe what each color means?
- Define your understanding of the following concepts: difficulty, popularity, prerequisites, and deadline overlaps.
- Now assign the values that you think are most appropriate to display the subjects
- How do you think the values affect the distribution of subjects on the map?
- Click on “Recommend Subjects” Can you tell us which subjects the system recommends?
- Do you agree with the recommendation?
- What subjects would you recommend and why?
- Select the subjects that you think are most suitable for this student's enrollment. In which weeks of the subject will the student have the greatest workload?

After utilizing the tool, the advisor's feedback was solicited:

- What aspects did you like the most?
- What aspects would you improve?
- What features or elements would you add?
- Would you use the visualization tool to make enrollment recommendations?
- Would you like to make any other contribution?

The interview with the beta advisor revealed mixed results. The advisor initially struggled to understand the map and subject order at a glance. Only after referring to the legend did their comprehension improve. Similarly, the advisor couldn't readily interpret the sliders, but their understanding increased after reading the associated explanations. The concept of "distance between subjects" appeared to be quite complex. Regarding the recommendation system functionality, the advisor agreed with four out of the six suggested subjects. While the calendar visualization was easily recognizable, it was recommended to use specific dates instead of weeks. However, the advisor found the visualization of deadline overlaps and the record tab with subject failure history to be very helpful. Notably, the advisor's understanding of the tool improved significantly after twenty minutes. The learning dashboard was ultimately viewed as a valuable resource, particularly for new advisors and students. The advisor expressed particular interest in the deadline schedule display and the student record tab, as accessing this information is currently cumbersome with the existing tools.

The beta advisor interview reinforced the importance of subject enrollment for a successful semester. Poor enrollment choices can significantly impact student progress. This finding aligns with data collected in previous sections. Currently, advisors struggle with scattered and sometimes inaccessible information sources, such as individual subject deadline schedules. A key advantage of the proposed learning dashboard is its ability to consolidate a wealth of information into a single, unified dashboard.

Following the initial advisor interview, several adjustments were made to the protocol. Firstly, to enhance understanding prior to the video call, an explanatory video of the tool was provided. Additionally, the number of student records delivered to each advisor was increased to four. This variation aimed to expose advisors to the diverse ways student academic records can be displayed and allowed for more in-depth exploration of the tool's functionalities. We placed particular emphasis on understanding advisor recommendations against the ones proposed by the recommendation system. This included investigating the alignment between the system's recommendations and the advisors' own suggestions.

- **Alignment:** How often did the system's recommendations coincide with the advisors' own suggestions?
- **Influence:** Did the recommendation system or the calendar view impact the advisors' recommendations after using the tool?

To conduct this evaluation, the UOC advising department notified all advisors of the existence of this project. Eight advisors expressed interest and volunteered to participate. The evaluation process mirrored the one used with the beta advisor, incorporating the previously outlined modifications. These modifications included:

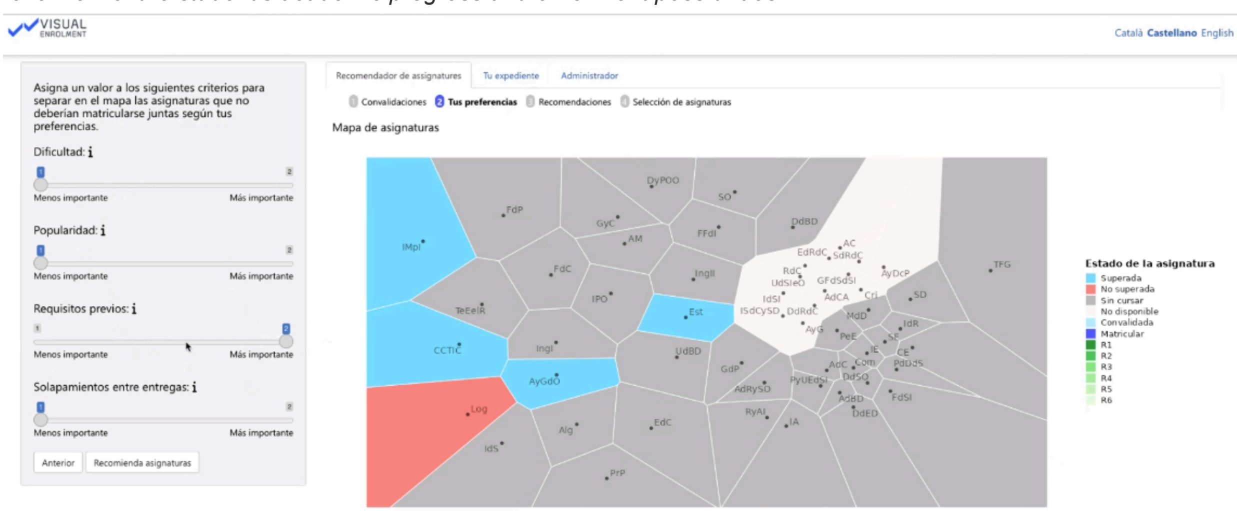
- **Pre-interview resources:** Advisors received an email containing four student records, a link to a Google Forms pre-questionnaire, and an explanatory video demonstrating the tool's functionalities.

- **Post-questionnaire interview:** Following completion of the pre-questionnaire, each advisor participated in a personalized interview. During the interview, the advisors' recommendations for the provided student files were compared to the recommendations generated by the recommendation system.

We used eighteen student academic records, with selection criteria including variation in student achievement. Two student records were common to all advisors: one with one failed subject and no validated subjects (see Figure 5.27), and another with all subjects passed and one validated subject. The remaining sixteen student academic records assigned to each advisor were entirely diverse, with the number of validated subjects ranging from one to seven, and nine of the sixteen records containing failed subjects. To ensure a diverse range of experiences for each advisor and encourage a variety of results, we distributed the student records such that each advisor received records with a mix of passed, failed, and validated subjects. After that, the eight interviews were performed and recorded, and the resulting audio recordings were transcribed to create written transcripts. These transcripts were then coded thematically to identify recurring concepts.

Figure 5.27 - Prototype used with advisors

Learning dashboard used in the interviews with advisors. We displayed the same student record, providing an overview of the student's academic progress and enrollment possibilities.



5.4.2 Results

This section commences with a review of the pre-interview questionnaire results. We will then delve into the interview findings, focusing on the most noteworthy aspects: Overall user experience, possible design changes, recommendation process overview, their experience as advisors and opinion changes. On one hand, an analysis of the pre-interview questionnaire revealed that all advisors consult each student's record and consider student's enrollment preferences. The importance of pre-enrollment interactions with students was highlighted in seven out of eight responses, while information regarding student grades emerged as another fundamental aspect mentioned in a similar number of responses. Notably, advisors consistently consider a student's previous number of subjects taken and passed before proposing enrollment counter suggestions. On the other hand, the responses indicated a consensus regarding the variable time investment required for reviewing enrollment proposals. This variation is largely attributed to individual student complexity. The process can range from 5 to 15 minutes for some students, while others with more intricate student records or proposals may require a significantly longer time frame. When multiple interactions are necessary, resolving the enrollment counter proposal on the same day may not be feasible.

Several open-ended responses provided valuable qualitative data, which can be found in Table 5.6. In addition to insights on prior assessments, three advisors identified shortcomings in the current advising tools. A common concern was the excessive complexity of the existing tool, requiring numerous clicks to access necessary student information. Conversely, a suggestion was made to develop a tool that highlights each student's passed subjects. Finally, one response pointed out the outdated design of the current enrollment proposal tool, hindering information visualization.

Table 5.6 - Open responses (current system)

Open responses related to the current enrollment system. Three advisors suggested improvements in the current advising tools.

Translated responses (in English)	Original responses (in Spanish)
Female, advisor since February 2010	
"(...) the excel that management provides is difficult to consult and is not always available, so we have to go to each subject study plan. It would also facilitate the process if the student's records were more accessible since we have to go through many links to get to them."	"(...) el excel que nos facilitan desde dirección es pesado de consultar y no siempre está disponible, por lo que hemos de ir a cada plan de estudios de las asignaturas. También facilitaría el proceso que los expedientes del estudiante estuvieran más a mano, pues hemos de pasar por muchos enlaces para llegar a los mismos."
Male, advisor since September 2010	
"(...) To be more efficient and make it more difficult to make mistakes, it would be good to develop a tool where you can see the subject dependency graph that appears on the advising site for each student, marking the subjects they have passed. "	"(...) Para ser mas eficiente y que sea mas difícil el cometer errores , estaría bien desarrollar una herramienta donde se vea el grafico de dependencia de asignaturas que aparece en el site de tutoría para cada alumno marcadas las asignaturas que tiene superadas."
Translated response (in English)	Original response (in Catalan)
Male, advisor since September 2016	
“My main comment would be that the registration proposal management tool has a completely outdated design and it is difficult to even see the columns and rows clearly in the lists.”	“Mi comentario principal sería que la herramienta de gestión de las propuestas de matrícula tiene un diseño totalmente anticuado y es difícil incluso ver en los listados las columnas y filas de forma clara.”

Following the interviews with advisors, the analysis explored how the tool addressed some of the previously identified issues. Overall user experience (UX) received positive feedback (Table 5.7). Advisors consistently mentioned a clear understanding of subject colors, facilitating a quick grasp of each student's record. However, while the underlying concepts of the criteria were readily identified, the concept of distance between subjects was proved less understandable. In contrast, the calendar visualization was considered a success, with most elements being well-understood. Notably, more than half of the advisors found the tool highly valuable, and seven out of eight indicated it would influence their workflow positively.

Table 5.7 - Advisors' feedback about user experience
Advisor feedback (N=8) on the overall user experience of the learning dashboard. Positive perceptions and areas identified for potential improvement are included.

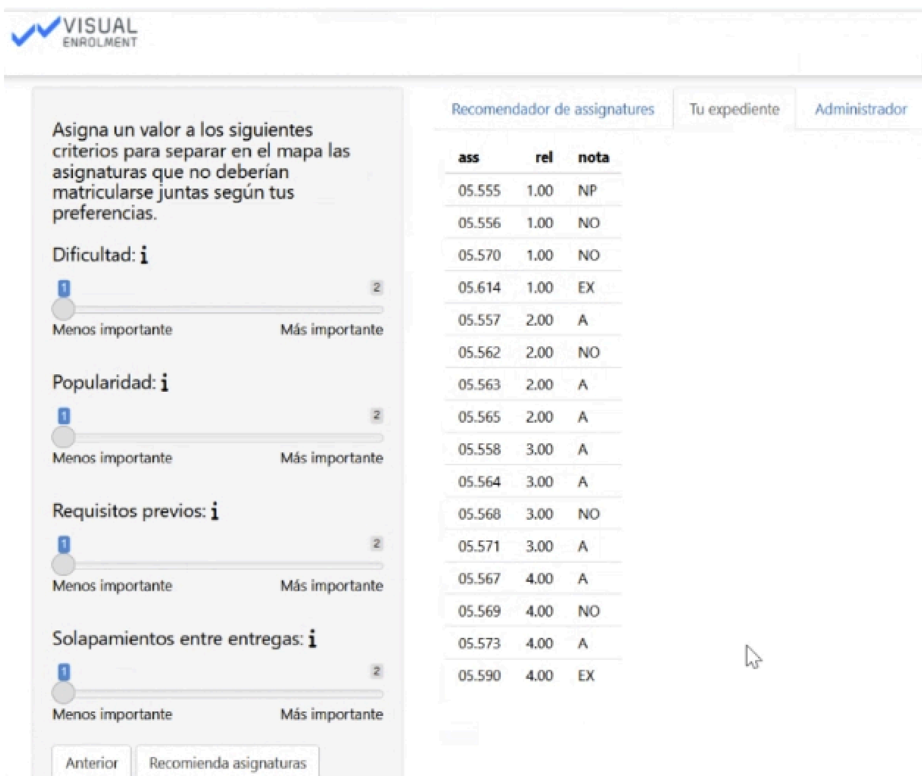
Advisors' perceptions	Mentions in interviews
Color selection is generally understood	8
The concept of difficulty is understood	4
The concept of popularity is understood	4
The concept of prerequisites is understood	8
Considers prerequisites a core value	8
The concept of overlaps between deliveries is understood	8
In general, the concept of distance is understood	0
In general, the most recommended subjects are understood	8
In general, it is understood when the student will have more deliveries	8
Viewing the number of days until deadline helps them understand the workload	8
Would use the visualization tool in their everyday tasks	8
Would like to use the tool as it is now	3
Finds subjects easily on the map	1
Clearly express that the tool changes this/her mind	3
Clearly express that the tool is very useful	5
Thinks that the tool makes you consider other options	7
Rate the visualization of the workload very positively	6

Advisor feedback on the tool design (Table 5.8) highlighted several key areas. Firstly, advisors emphasized the importance of displaying the full names of subjects. Secondly, they expressed a strong desire to access a student's historical academic record directly within the tool. Most surprisingly, the table view of the students' academic record (Figure 5.28) emerged as the most frequently used and highly valued feature, surpassing its anticipated role within the learning dashboard.

Table 5.8 - Advisors' feedback about design
Relevant qualitative data (N=8) regarding design.

Advisors' perceptions	Mentions in interviews
Would like to see the full name of the subjects	7
Would like to see the historic student record	5
Constantly uses the student record tab	8

Figure 5.28 - Example of academic record
It indicates the subject (with a code), the relative semester and the grades obtained by the student.



Furthermore, advisor feedback revealed an interesting aspect of the recommendation process: most advisors consider student opinions crucial to perform their enrollment proposal feedback (Table 5.9). In other words, prior enrollment proposals submitted by students are essential for effective advising, not just the student's academic record. This emphasis on knowing student preferences beforehand proved highly relevant during the next evaluation phase, which incorporated students into the process (Chapter 6).

Table 5.9 - Advisors' feedback about recommendations
Relevant qualitative data (N=8) regarding the recommendation process.

Advisors' perceptions	Mentions in interviews
Would like to know the student's opinion before making a recommendation	7
The system should automatically add the validated subjects	2

Table 5.10 presents qualitative data on advisor experiences related to subject recommendations. A key finding is the strong emphasis advisors place on considering previously validated subjects during the recommendation process. However, the feedback regarding the map-based visualization tool was mixed. While some advisors found the concept interesting, others expressed a preference for a design more similar to an official document provided by management (Figure 5.26). This suggests a potential need for further refinement or alternative visualization options, as well as some reticences utilizing new tools (Klein et al., 2019). It is also important to note that the institution already utilizes recommendation systems like the ESPRIA package (González et al., 2018). This package focuses on streamlining the enrollment process by suggesting predefined subject groups to students beginning their degree program.

Table 5.10 - Advisors' feedback about overall experience
Advisor feedback on their overall experience using the learning dashboard (N=8), focusing on their interactions with students, the degree program, and the institutional tools they utilize.

Advisors' perceptions	Mentions in interviews
The concept of difficulty depends on each student	3
Applies less than 7 days until deadlines	3
Applies 7 to 14 days until deadlines	4
Applies more than 14 days until deadlines	1
Constantly refers to the UOC recommendations pdf	4
Uses ESPRIA package to recommend	2
Thinks that validated subjects should be a factor in recommendation	8
Express concern about itineraries	2
Thinks that the learning dashboard should be used only by advisors	1

Finally, Table 5.11 explores how the tool influenced advisor recommendations. Interestingly, advisors changed their initial recommendations in 24 out of 32 cases after using the tool. However, only 14 of these revised recommendations aligned with the system's suggestions. The primary reason for these discrepancies appears to be the system's inclusion of subjects with prerequisites, which advisors may not have initially considered. In contrast, the calendar view emerged as a clear success. Advisors found the subject schedules persuasive in most cases, with only one advisor expressing disinterest in this second visualization. This suggests a high level of advisor engagement with the calendar functionality.

Table 5.11 - Impact of recommendations
Impact of visualization on subject recommendations (N=32).

Advisors' perceptions	Mentions in interviews
Changes recommendation when visualizing the map	24
The recommendation seems appropriate	14
Changes recommendation when visualizing the calendar (13/32) or the selected subjects produced an already acceptable calendar (13/32)	26

5.4.3 Learning dashboard improvements

Advisor insights from the beta test and subsequent interviews underscore the critical role enrollment plays in a student's semester success. As demonstrated in previous sections, data confirms that poor enrollment choices can significantly hinder student outcomes. While advisors act as a key confirmation point for student enrollment decisions, their access to crucial information can be difficult or even unavailable. This includes vital details like student records and subject I deadline schedules. Further complicating the process, students prioritize different criteria when making enrollment choices, which may not always align with their advisor's recommendations.

This first evaluation involving advisors revealed that the learning dashboard effectively presents a comprehensive view of the study plan within a single visualization. The map metaphor was well received by advisors, allowing them to grasp the student's academic record efficiently. While no single tool caters perfectly to all users, the feedback suggests that this dashboard offers valuable new functionalities and demonstrably supports advisors in their decision-making processes, allowing them also to consider further options.

Informed by advisor feedback, several key improvements were implemented to enhance the tool for the final student test (see Table 5.12). A prominent example is the preconfiguration of the prerequisite slider to its maximum value upon opening the tool, reflecting the advisors' emphasis on this criterion. Building on the positive reception of the students' academic record table, its readability was further improved. Additionally, a roll-over pop-up was implemented to enhance the readability of the subjects within the map visualization. This pop-up displays the full name of the subject along with other pertinent information.

Table 5.12 - Proposed changes (implemented)
Summary of changes in final development iteration (N=8).

Design Feature	Changes	Mentions in interviews
Validated subjects	Validated subjects can be marked regardless of whether they are available that semester	2
Recommendation system	Give importance to prerequisites	8
Student record tab	Add subject names	6
	Change acronyms for complete ratings (*NO* for *Notable*)	2
Subject roll-over pop-up	Add full name of subjects to the roll-over pop-up	8
	Delete semester number	2

Table 5.13 - Proposed changes (pending)
Summary of unimplemented prototype changes (N=8).

Design Feature	Changes	Mentions in interviews
Validated subjects	Validated subjects are automatically marked	2
Map visualization	The subjects appear with the full name	6
	Change Voronoi display	8
	See the historical map (my marks)	5
Recommendation system	Recommend algebra immediately after introduction to mathematics	3
	Give importance to validated subjects	8
	Give importance to failed subjects but not to those that have not been presented	1
	Try to recommend basics first, then mandatory and then optional	1
Subject roll-over pop-up	Add difficulty from 1 to 5	1

Nevertheless, while the evaluation identified several potential improvements, not all of them could be incorporated before the final validation (Table 5.13). For instance, an automatic marking of validated subjects functionality was not feasible. The subject validation process can be time-consuming, resulting in most students not having them recorded when enrolling. Furthermore, while considering previously validated subjects might seem intuitive for subject recommendations, this approach can be challenging. We lack information about a student's current knowledge retention in those subjects. Therefore, prioritizing validated when recommending subjects could delve into less adequate recommendations. We also decided on the exclusion of other overly specific criteria, such as giving importance to failed subjects but not to those that have not been presented or recommending specific subject sequences (i.e. recommend algebra immediately after introduction to mathematics). The recommendation system already prioritizes basic subjects in a general sense as it takes into account the degree structure when placing the subjects, although it is not explicit in the learning dashboard design. Similarly, the decision was made to retain the current map visualization based on a cost-benefit analysis. On the one hand, the map effectively allowed advisors to view student files at a glance and recommend subjects based on identified "gaps" in their enrollment plans. Furthermore, the ability to select subjects and generate a secondary visualization was perceived as a valuable functionality by advisors.

A key modification planned for the final learning dashboard and recommendation system validation involves integrating student-advisor interaction into the recommendation process. Recognizing the importance advisors place on student input, we aim to test the tool within a more realistic workflow. This would involve students utilizing the learning dashboard to make initial enrollment decisions, followed by advisor review and feedback. This approach has a two-fold purpose:

- **Evaluate student interaction with the tool:** We can assess how students engage with the learning dashboard and gauge its influence on their enrollment choices.
- **Leverage advisor expertise:** By incorporating advisor feedback on student-generated enrollment plans, we can leverage their knowledge and ensure the tool effectively complements the existing advising process.

5.5 Summary

This research project successfully developed a learning dashboard to assist in making informed enrollment decisions at an open online university. By following an iterative design approach and incorporating user-centered design principles, the project effectively identified key student information needs and developed a tool that addresses those needs. The research process involved data collection, design proposals, prototype development, and ongoing evaluation and refinement. Through these steps, a learning dashboard was designed to provide students and advisors with valuable information and support their decision-making process. The creation process of this learning dashboard involved several key stages:

1. **Identifying student information needs:** Through data analysis and student interviews, the project identified critical factors influencing student decision making, including available study time, prior academic experience, completed subjects, prerequisites, subject difficulty, scheduling conflicts, and subject popularity.

2. **Design proposals and iterations:** Various design proposals were explored, taking inspiration from existing visualizations. Iterative design processes were employed to incorporate user feedback and refine the learning dashboard.

3. **Key design considerations:**

- **Visual representation:** The learning dashboard should visually represent the degree program as a map, allowing students to visualize already taken subjects and understand their progress within the degree.
- **Subject relationships:** The visualization should clearly depict dependencies and relationships between subjects, being able to adapt them to student preferences.
- **User interaction:** The dashboard should be interactive, allowing students to personalize their view by adjusting factors like subject difficulty, popularity, previous requirements and overlaps between deadlines.
- **Data integration:** The dashboard should integrate relevant data, such as student academic records and subject information.

4. **Prototype development and evaluation:** A proof of concept prototype was created and evaluated through advisor interviews and usability testing. Feedback from these sessions informed further iterations and refinements of the design.

5. **Final learning dashboard:** The final learning dashboard incorporated the key features identified through the research process, providing students and advisors with a visually engaging and informative tool to support their enrollment decisions.

The recommendation system developed for the learning dashboard utilizes an algorithm to suggest subjects that align with students' academic progress and preferences. By analyzing factors such as difficulty, popularity, previous requirements and overlaps between deadlines, the system calculates distances between subjects and recommends those closest to the student's completed subjects. Students can personalize the recommendations by adjusting the weights assigned to different criteria. While the system demonstrates promising results, it's important to address challenges such as the need for continuous refinement to enhance its accuracy and effectiveness.

The proof of concept for the complete learning dashboard and all its features experimented several iterations and design explorations to create a visually engaging and informative tool. Key features included a map-based representation of the degree curriculum, subject placement based on relevant factors, user-friendly interactions for customization, a calendar view for visualizing deadline dates and workload, and ongoing user feedback to refine the design. Through these efforts, the learning dashboard demonstrated its potential to effectively support advisor decision making by providing a comprehensive overview of the degree curriculum, subject recommendations, and other essential information.

Hence, we have fulfilled the second research objective of this thesis: Develop an effective representation of enrollment-related data that allows both students and advisors to access relevant information related to the enrollment process. The learning dashboard developed in this research provides a valuable tool for supporting student and advisor decision making during the enrollment process. Key features and considerations include:

- **Viewing the academic record at a glance:** The use of a map to represent the degree curriculum and the student academic record offers a clear and intuitive visualization.
- **Subject placement:** Subjects are positioned on the map based on their relationships and relative distances, considering factors like difficulty, popularity, prerequisites, and overlaps between deadlines.
- **User interaction:** The dashboard allows users to customize the map by adjusting factors and viewing subjects in different categories.
- **Calendar integration:** A calendar view provides information about subject deadline dates and workload. This has been proven a highly valuable tool for advisors.
- **Recommendation system:** The integrated recommendation system suggests subjects that align with students' academic progress and preferences.
- **Data integration:** The dashboard incorporates relevant data, including student academic records, subject information, and enrollment requirements.

By combining these elements, the learning dashboard allows students and advisors to make informed enrollment decisions by providing a comprehensive overview of the degree curriculum, subject recommendations, and relevant information in a visually engaging and interactive manner.

Chapter 6
Prototype validation

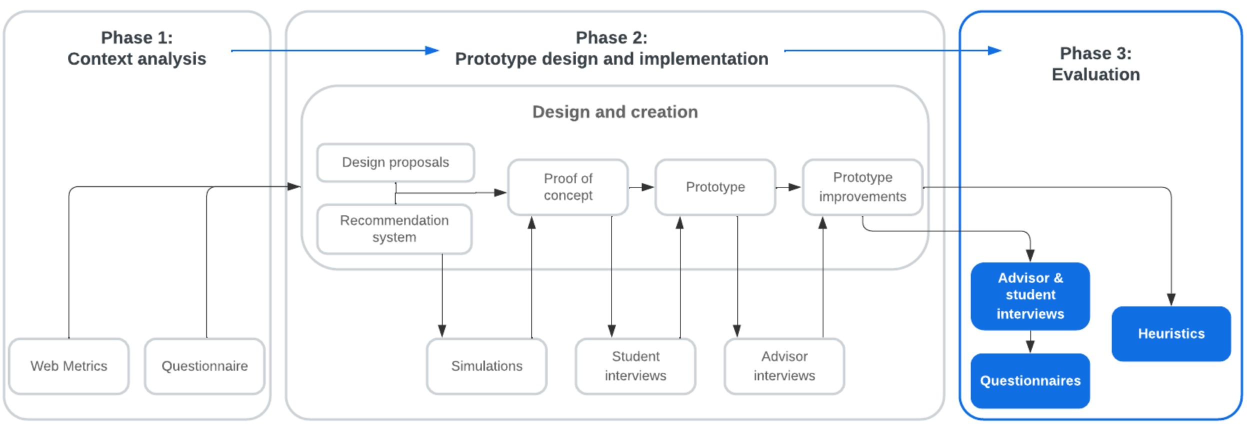
This chapter describes the validation process of the prototype developed in Chapter 5. The process incorporated insights from prior interactions to refine the methodology. It includes a preliminary student questionnaire, extensive interviews with students and advisors, and separate final questionnaires for both student and advisors. This chapter will address the third research question of this thesis: *To what extent is the use of a learning dashboard with a recommendation system relevant for the decisions taken by students and advisors when enrolling?*

6.1 Introduction

Chapter 4 presented the methodology employed for gathering information used in the design and development of the prototype, which was detailed in Chapter 5. However, the prototype, although created taking into account all available data, had not yet been tested with students. To assess the learning dashboard's efficacy, a comprehensive validation process was undertaken as shown in Figure 6.1. This process incorporated two types of users, specifically students and advisors within the UOC's Computer Science program.

Figure 6.1 - Diagram of project phases (phase 3)

Research process informed by Oates (2006). In this chapter we focus on the prototype evaluation by means of interviews, questionnaires and a heuristic study.



Data collected from prior interactions played a pivotal role in shaping the validation process. This data included not only quantitative information –web metrics and proof of concept simulations– but also qualitative insights derived from student questionnaires, informal interviews with students and in-depth interviews with advisors. This information was used for both the development and refinement of the final prototype, and further served to establish this last validation process. A key distinction from previous evaluations presented in previous chapters lies in the incorporation of two clearly differentiated stakeholders into the study: students and their advisors. Recognizing that these users have distinct goals and informational needs when interacting with the prototype is crucial (Abras et al., 2004; Benyon, 2013). Beyond gathering individual user data, we also aim to determine whether the prototype facilitates communication between students and advisors, and if so, to what extent.

In order to incorporate both students and advisors, we must first understand their roles and stages within the enrollment process. As detailed in Chapter 4, students typically conduct independent research and select enrollment subjects on their own, following institutional recommendations to some extent. They may subsequently choose to inform their advisors about these selections, although this practice is not universal. After that, advisors review the student subject selection and provide feedback on their enrollment suitability based on the student's academic progress and program requirements. The validation process presented in this chapter will explore whether the prototype could influence the student's enrollment subject selection, the advisor's opinion on the student's choice, and if the learning dashboard could somehow impact this decision-making process. This validation process will also explore the possibility of advisors initiating enrollment proposals, even if students have not contacted them beforehand. This would represent a potential shift in the current enrollment process.

To integrate both students and advisors into the study, a protocol was designed that included individual surveys for each group and a joint interview to evaluate the prototype. The preliminary questionnaire yielded conclusive results from many of the participating advisors. As a result of this, the advisor questionnaire was excluded from the current validation process. Nevertheless, a preliminary questionnaire was designed to explore student motivations, as this data was previously absent (Section 6.3). Interviews and observations were also established, specifically tailored to incorporate both user groups (Section 6.4). After that, two separate final questionnaires were created, one for students (Section 6.5) and one for advisors (Section 6.6). Last of all, a heuristic test was performed with UX experts (Section 6.6) to ensure the learning dashboard's effectiveness and user-friendliness. This evaluation utilizes the knowledge and experience of a user interface design and usability specialist. By involving them after prototypes are built, the test allows for detection and correction of usability issues before full implementation. Additionally, a heuristic test with experts can identify problems that may have been missed.

With all these validation procedures, we would like to further explore the communication processes between students and their advisors to determine potential areas for improvement. These areas of improvement can be identified both in the current enrollment process and the one resulting from incorporating the learning dashboard.

6.2 Validation procedure

In addition to applying the Oates Research Process (Oates et al., 2006), we conducted comprehensive research on existing literature reviews on learning dashboards (Bodily & Verbert, 2017; Schwendimann et al., 2017). We aimed to analyze the different types of evaluation methods used for similar learning dashboard projects. The common evaluation methods identified included questionnaires, interviews, qualitative think-aloud studies, field tests, and focus groups. In Chapter 2, Table 2.2 reveals that questionnaires and interviews were the primary project evaluation methods employed. Notably, only one project incorporated advisors in the validation process and the number of participating users generally remained quite limited. Questionnaires and interviews were chosen as the primary evaluation methods for this project. By analyzing the reviewed learning dashboard projects in Schwendimann et al. (2017), we were able to extract the most appropriate question types for questionnaires and interviews. Based on this analysis, the following evaluation materials were created:

- Data Protection Consent form (Annex A.5.1).
- Announcements for the virtual campus board and explanatory email texts.
- An explanatory video demonstrating the prototype's functionalities.
- A preliminary student questionnaire (Annex A.5.2).
- The interview protocol for both students and advisors (Annex A.5.3).
- A final student questionnaire and a separate final advisor questionnaire (Annexes A.5.5 and A.5.6).

It is important to note that at the moment of performing this research, students had already enrolled and were taking the selected subjects. We used a retrospective approach to explore how they might have used the decision-making prototype. The following steps outline the participant recruitment process:

1. **Announcement:** The study was announced on the virtual campus forum, encouraging students to contact their advisors if interested.
2. **Data consent:** Students who expressed interest received and completed a data protection consent form.
3. **Preliminary questionnaire:** An email containing a preliminary questionnaire was sent to the participating students.
4. **Interview scheduling:** A convenient date and time for students and advisors was arranged for the interview.
5. **Final questionnaire:** A final questionnaire was sent to students and advisors after the interview.

To begin the study, we contacted the advisors who had participated in the previous interview. Of the eight initial advisors, seven expressed their intention to continue participating in the study. One of the advisors could not continue to participate due to lack of time. In addition, the program director contacted the advisors again and two more advisors volunteered, making a total of nine advisors. In order to recruit student participants, an announcement was posted on the virtual campus forum inviting interested students to contact their advisors. Upon expressing interest, students received and completed a data protection consent form, ensuring their participation was voluntary and their data would be handled ethically. Scheduling interviews required coordinating availability between advisors and students, so the interviews could be synchronous. The validation procedure involved twenty-seven students (three women, 24 men) and nine advisors (four women, five men). Although the target was set at 36 students and 37 signed up, ten students were discarded for various reasons. The main reason was that many depended on a single advisor and we could not take that much of his time. Furthermore, we tried to avoid biasing the responses by limiting them to a single advisor. Other students ultimately decided not to participate. At the end, between one and five students were interviewed with each advisor. We aimed for a more balanced gender distribution among students, but the Computer Science program demographics has a typically higher proportion of male students. A previous study analyzing data on UOC's Computer Science graduates from the 2009-10 academic year to 2021-2023 placed the percentage of female graduates at 10.4% (Minguillón et al., 2023). All participants volunteered their time and received no compensation. Students were in different stages of their academic journey within the degree at the time.

Twenty-five students had validated subjects. Another fifteen students had not passed one or more subjects. This distribution reflects the diverse academic progress of the students participating in the validation procedure, as can be seen in Table 6.1. Figure A.6 illustrates the diversity of student academic backgrounds revealed through the learning dashboard generated maps (maps depicting students' academic records and validated subjects). Table 6.1 reflects the key academic progress indicators of the students who participated in the study. The number of semesters and credits completed is completely different. Some students have finished their second semester at the UOC and others have been studying for nineteen semesters, probably taking only one subject per semester. Therefore, the students have progressed differently in their academic careers, being at the beginning, mid-career, or about to end. This disparity aligns with the typical UOC student profile and enrollment data. As expected, each student possesses a unique and intricate academic journey, driven by various motivations for pursuing the degree.

Table 6.1 - Academic progress indicators

Key indicators of student academic progress. The wide ranges reflect the different student situations within the degree.

Academic progress indicators	Range	Median	Mode
Number of completed semesters	2 to 19	6.37	8
Passed credits	36 to 222	122.67	156
% Program completion	15% to 93%	51.11%	N/A
Number of validated subjects	0 to 16	11	11
Number of subjects students had enrolled in	1 to 6	2	2

The **preliminary questionnaire** (see Annex A.5.2) explored student decision-making processes during subject enrollment at the UOC. Questions 1-3 gathered information on the factors that students consider when choosing subjects and the number of subjects they enroll in. Question 4 delved into student preferences for retaking failed subjects. Questions 5 and 6 investigated how students utilize the institutional study plan and the influence of academic advisors. Questions 7 and 8 assessed student self-confidence during the enrollment process and their overall satisfaction with the experience. Finally, question 9 provided an open-ended opportunity for students to share any additional insights on the enrollment process. While a substantial amount of students' enrollment data has been gathered throughout this thesis, certain key questions remain unanswered. In the case of students, for example, the total number of subjects in which they have already enrolled is known. However, to gain a deeper understanding of the student decision-making processes prior to introducing the prototype, it would be valuable to explore the following:

- **Subject selection rationale:** Beyond the identified prioritization of re-enrolling in failed subjects, what factors influence student subject selections? This could include considering factors like preferred semester structure and advisor recommendations, among others.
- **Self-confidence:** We currently lack information about students' level of confidence in subject selection before interacting with the prototype.

Moreover, informal student interviews had previously been conducted regarding the prototype's basic functionalities (as described in Section 5.3.2). However, as students were shown merely a proof of concept, further testing with the finalized prototype was necessary. In contrast, many advisors were already familiar with the learning dashboard and recommendation system due to their participation in the study presented in Section 5.4.1. However, their response to using the prototype collaboratively with their students remained unknown. To evaluate both user experiences combined within the final version of the prototype, an interview was implemented. This interview explored student and advisor experiences with the prototype learning dashboard that incorporated a recommendation system, applied to the UOC enrollment process (Annex A.5.3). The interview tried to reproduce in a synchronous way what would asynchronously happen in a real scenario.

In summary, during the interview, students were shown their academic record which was displayed on the dashboard. After that, they evaluated the added value of the visualization, providing insights into the information representation. Following a system recommendation for six subjects, these recommendations were compared to their actual choices. This comparison revealed any discrepancies between the system's recommendations and the student's final decisions. The students also indicated their preferred subject selections based on the system's recommendations. Furthermore, the students participated in a visualization exercise, selecting subjects deemed suitable for their previous enrollment. Additionally, students provided information on their typical workload, specifically the number of days they spent preparing for their subject deadlines. On top of all of this, we incorporated the advisor's standpoints into the interview as they reviewed the student's subject selections and offered their own feedback, indicating any potential changes they might recommend. Following the utilization of the prototype, the student and advisor discussed its effectiveness as a collaborative decision-making platform during enrollment. They identified the aspects they liked most, the areas for improvement, and potential features for future development. Finally, both stakeholders were also asked for their willingness to use the visualization prototype for future enrollments and offered any additional thoughts on the experience.

The final questionnaire assessed user experience for both students and advisors. It measured four key aspects, based on the Technology Acceptance Model and adapted to learning dashboard projects (Rienties et al., 2018; Vasnier et al., 2020), namely perceived ease of use, perceived usefulness, overall acceptance of the learning dashboard, and student and advisor perceptions of the main design features. The questionnaire provided to students will be described first and can be consulted in Annex A.5.5.

Perceived ease of use:

- **Information clarity:** Question 1 asked if they found the information easy to understand and interpret, followed by an open-ended prompt for them to elaborate on their reasons.
- **Usability:** Question 2 evaluated the overall user-friendliness of the dashboard. Students were asked to rate the prototype's difficulty level (easy or difficult) and explain their reasoning.

Perceived usefulness:

- **Decision making:** Question 3 asked if the prototype made the process easier or more efficient, with a follow-up question for them to explain their experience.
- **Recommendation accuracy:** Question 4 explored student perceptions of the recommendation system. Students were asked whether they believe the prototype provides appropriate subject recommendations and to explain their reasoning.

Acceptance:

- **Intention to use:** Question 5 asked if they would utilize the prototype for the next semester enrollment and to explain their decision.
- **Most valuable feature:** Question 6 identified the feature or functionality students found most relevant during their enrollment process (e.g., map, sliders, calendar).
- **Advisor consultation:** Question 7 assessed whether students would still seek guidance from their academic advisor even with the learning dashboard available. Students were encouraged to explain their reasoning.

The final questionnaire for students also included an overall satisfaction rating with the enrollment experience, including the use of the learning dashboard and an open-ended question to provide additional feedback. This final question provided an opportunity for students to share any additional thoughts or suggestions they may have regarding the learning dashboard or the enrollment process in general.

The advisor questionnaire mirrored the student survey, with a key difference in Question 7 (Annex A.5.6). This question focused on the potential for proactive advising by using the learning dashboard. Specifically, it asked advisors whether they could make a registration proposal using the prototype before the student contacted them and were encouraged to explain their reasoning.

Knowing the opinions regarding the learning dashboard and recommendation system of both stakeholders is crucial for research purposes and future studies. On the one hand, the advisor's final questionnaire explored their perceptions of the prototype, including the most relevant elements, any missing information, and whether the prototype facilitated the decision-making process. The most critical question addressed the potential for the prototype to enable advisors to initiate enrollment proposals for students, even before being contacted by them. On the other hand, the student final questionnaire focused on their user experience, including their opinions regarding the prototype, the most relevant elements and any missing information. The key question for students investigated whether they perceived the advisor's role in the enrollment process to remain relevant after using the prototype. This question, which may appear somewhat contentious, is nevertheless grounded in data collected throughout previous chapters. As evidenced in the Chapter 4 questionnaire, students surprisingly ranked advisors as the least relevant source of information during enrollment.

Once all the data was collected from the questionnaires and interview transcripts, thematic coding was applied to categorize participant responses. After that, the frequency of each theme was analyzed to draw conclusions from each data collection method. In the following sections, we explore the results obtained through each research method.

To ensure our proposed enrollment decision-making prototype adheres to best practices and delivers an optimal user experience, we opted for a heuristic evaluation conducted by a panel of user interface design experts. This approach leverages the established framework of the 10 Usability Heuristics (Nielsen, 2024), which provide a comprehensive set of guidelines for user interface design. These heuristics encompass key principles like maintaining clear visibility of system status (1), ensuring the interface aligns with real-world conventions (2), and empowering users with control and freedom during interaction (3). By systematically evaluating the prototype against these principles, our expert reviewers can identify potential areas for improvement in terms of consistency (4), error prevention (5), and promoting user recognition over memorization (6). Additionally, the evaluation will assess the prototype's flexibility and efficiency for various user needs (7), while advocating for an aesthetically pleasing yet minimalist design (8). Finally, the heuristics address user support by ensuring the prototype incorporates mechanisms to help users recognize, diagnose and recover from errors (9), and offers appropriate help and documentation resources (10). All the questions designed for this method can be found in Annex A.5.7.

6.3 Student preliminary questionnaire results

The preliminary questionnaire investigated student decision making during the UOC subject enrollment. It explored factors influencing subject selection, preferences for retaking failed subjects and the role of study plans and academic advisors. Finally, the questionnaire assessed student self-confidence during enrollment and their overall satisfaction with the process (without using the learning dashboard prototype). Having established the importance of time management in Chapter 4, the results of this questionnaire align with previous findings. As shown in Table 6.2, prioritizing time management remains a key theme in student responses (17 out of 27 students mentioned it). Similarly, the trend of students favoring subjects they had not passed yet observed in Chapter 5 simulations is further corroborated by the present data (it appears in 23 out of 27 responses).

Table 6.2 - Student's standpoints (about enrollment)
Students' standpoints on enrollment regarding the number and specific subjects into which a student enrolls before using the learning dashboard (N=27).

Students' standpoints	**Mentions in questionnaire**
The reason why I have enrolled in X subjects has been because of the available time I have (combining studies with other activities)	**17**
The reason why I have enrolled X subjects has been economic	1
The reason why I have enrolled in X subjects has been due to the recommendation of the advisor	1
I prefer to wait to enroll in subjects that I have failed	3
I prefer to enroll in the subjects that I fail immediately	**23**
I follow the pre-established order in the study plan	12
I do not follow the pre-established order in the study plan	11
Sometimes I follow the order of the study plan and sometimes I don't	5
I have never changed my enrollment when consulting with the advisor	9
I have never changed my enrollment after consulting with the advisor	**18**
My enrollment choices were clear from the beginning	**16**
I evaluate different options before enrolling	9
Average grade of the enrollment process without using the learning dashboard	**7,63**

Nevertheless, while the Chapter 4 questionnaire showed that advisors were the least valued information source, the questionnaire revealed that 18 out of 27 students changed their minds after consulting an advisor in one or more previous enrollments. Furthermore, 16 out of the 27 participants already had a clear enrollment plan beforehand. These findings suggest that advisors are not necessarily the primary information source, but rather a crucial resource for students to solve enrollment uncertainties, obtain second opinions, or confirm their subject selections to avoid mistakes. Student open-ended responses further supported these findings. When expressing positive views on advisors (Table 6.3), students highlighted their role in enrollment confirmation and modification. Often, when students advance and feel more confident in their academic trajectory, they become more independent, relying on advisors primarily for confirmation of their subsequent enrollments.

Table 6.3 - Open responses (about advisors)
Open responses related to favorable opinions regarding the advisor role.

Translated responses (in English)	Original responses (in Spanish)
Male participant in the 8th semester, enrolled in three subjects[2]	
“Normally I wait for the advisor report to vary or not the enrollment. The last one I neglected the study plan and I had to take on more complicated subjects (in my opinion) but they are necessary at this time.”	“Normalmente espero a su informe para variar o no la matrícula. La última descuide el plan de estudios y tuve que asumir asignaturas más complicadas (a mi parecer) pero que son necesarias en estos momentos.”
Male, 4th semester, six subjects	
“Initially the advisor sent me his recommendations and to a certain extent I followed his criteria but made changes to adapt it to my personal circumstances. His recommendation, I think very well motivated, was that I work between 3 and 4 subjects per semester but I trusted my ability to work and decided to do between 5 and 6 subjects per semester. For the rest of the registrations, except for one that I forgot to ask him about, my proposals always seemed appropriate and in line with my career. ”	“Inicialmente el tutor me envió sus recomendaciones y en cierta medida seguí sus criterios pero hice cambios para adaptarlo a mis circunstancias personales. Su recomendación, creo que muy bien motivada, era que trabajara entre 3 y 4 asignaturas por semestre pero confiaba en mi capacidad de trabajo y decidí hacer entre 5 y 6 asignaturas por semestre. El resto de las matrículas, salvo una que olvidé consultarle, mis propuestas le parecieron siempre adecuadas y en línea con mi trayectoria. ”
Male, 11th semester, one subject	
“The proposal has only been modified once by the advisor, and it made a lot of sense because it was only taken during the first semester”	“La propuesta, solo me la han modificado una vez la tutora, y tenía mucho sentido porque solo se cursaba durante el periodo del semestre 1”
Male, 4th semester, four subjects	
“My advisor has advised me to do some subjects before others, or to be careful with the workload of a specific subject, and he was right, so I trust his judgment, and I take it into account.”	“Mi tutor me ha aconsejado realizar alguna asignatura antes que otra, o que tenga cuidado con la carga de faena de una asignatura en concreto, y tuvo razón, de tal forma que confío en su criterio, y lo tengo en cuenta.”

Analysis of unfavorable advisor comments shown in Table 6.4 suggests that some students perceived the advice as repetitive of information already available on the study plan website, or irrelevant due to their specific situation involving validated subjects with potentially different academic processes. This could be caused by limitations in advisor access to student data in certain scenarios, especially in the case of potential validated subjects that are not yet present in student records. Nevertheless, some open responses related that some students created their own enrollment tools, as shown in Table 6.5. This is a compelling argument for the learning dashboard development's value. It demonstrates a clear student desire for a different enrollment tool, which the proposed project aims to address effectively.

[2] From this point forward, the information of the students in the study will be summarized in the following format: *Male, 8th semester, three subjects.*

Table 6.4 - Open responses (highlights about advisors)
Open responses highlighting challenges in the academic advising process.

Translated responses (in English)	Original responses (in Spanish)
Male, 10th semester, three subjects	
“The advisor relies on the list of recommendations, so he does not add value in that sense.”	“El tutor se basa en lo que pone en la lista de recomendaciones, por lo que no aporta valor en ese sentido.”
Male, 7th semester, one subject	
“Sometimes he has made a suggestion to me ("enroll in this other subject first") but I have rejected it because I was in the process of validating those subjects because of my work experience”	“Alguna vez me ha hecho alguna sugerencia ("matricúlate de esto otro antes") pero la he desestimado porque estaba en procesos de convalidaciones de esos contenidos por experiencia laboral”

Table 6.5 - Open responses (about student’s tools)
Students’ responses on developing their own tools to analyze their enrollment plan.

Translated responses (in English)	Original responses (in Spanish)
ale, 10th semester, three subjects	
“(...) I have an Excel document to make simulations about the subject order I should take when enrolling.”	“(...) Tengo un excel para hacer simulaciones sobre el orden que debería tomar en la matrícula.”
Female, 8th semester, two subjects	
“(...) I have my own subject plan and I choose according to the UOC recommendations, the difficulty, the time I have available and the subjects I have not taken.”	“(...) Tengo mi propio plan de asignaturas y elijo según las recomendaciones de la UOC, la dificultad, el tiempo que tengo disponible y las asignaturas que me van faltando.”
Male, 4th semester, four subjects	
“Once the information has been analyzed according to the guidelines described and using as a basis the indicated document and a table of my own creation, I usually have a clear idea of the enrollment. Despite this, in 2021/1 I made an enrollment modification since for personal reasons I initially took only 1 subject and finally took 2.”	“Una vez analizada la info según las pautas descritas y usando como base el documento indicado y una tabla de mi propia elaboración, suelo tener clara la matrícula. A pesar de ello, en 2021/1 realicé una modificación de matrícula ya que por motivos personales inicialmente cogí solo 1 asignatura y finalmente cursé 2.”

Finally, as can be seen in Table 6.2, the average rating for the enrollment process without the learning dashboard is 7.63. This data serves as a baseline for evaluating the prototype's impact. We will assess whether the prototype improves or worsens the enrollment experience for the 27 students by comparing their pre- and post-prototype usage perceptions. In conclusion, the preliminary questionnaire findings reinforce the value of the proposed learning dashboard by highlighting three main key takeaways:

- **Specifications on the advisor's role:** We now know that the advisor is not merely a source of information for students and how they utilize their guidance during the enrollment process.
- **Enhanced advisor support**: The questionnaire underscores the need for improved advising tools during enrollment. The learning dashboard could equip advisors with a more comprehensive view of student academic records, including validated and pending validation subjects, that might allow them to provide a more informed guidance.
- **Providing students with an enrollment learning dashboard:** The questionnaire also reveals that some students resort to creating their own enrollment tools. The proposed learning dashboard might solve this need.

6.4 Interview and observation results

This section describes student and advisor experiences with the learning dashboard prototype. The interview was designed to investigate its effectiveness as a collaborative enrollment prototype, supporting the current enrollment procedure. Students evaluated the dashboard's presentation of their academic record and compared system recommendations to their actual subject selections. They also participated in a visualization exercise and provided workload information. After that, advisors reviewed the student's selections and offered feedback. Finally, both students and advisors discussed the prototype's strengths, weaknesses, and potential for future use in the real enrollment process. As shown in Table 6.1, students represent a wide range of academic backgrounds and circumstances within the program. This diversity is evident not only in the chapter's conclusions, but also in the student enrollment records depicted in the generated maps. For a detailed view of these maps, refer to Annex A.5.4.

Table 6.6 - Student’s standpoints (about the map)
Students’ standpoints on map visualization (N=27).

Students’ standpoints	Mentions in interviews
The student identifies their academic record	21
The map gives a global idea of the degree and helps the student understand the subjects they have already completed and those they have not taken	19
Acronyms are not understood or make it difficult to identify subjects	16
The map should represent the prerequisites explicitly	10
The student believes that the subject area has some kind of meaning	7

Table 6.6 reveals a range of student standpoints on the visualizations of their academic records transformed into maps. While some students expressed diverse opinions, a common theme emerged: Most students recognized their academic journey reflected on the map. They found the map helpful in providing a complete view of their academic record and program progress, including validated, completed and pending subjects. This aligns with the intended purpose of the visualization prototype, as outlined in Chapter 5.

Table 6.7 - Open responses (positive about the map)
Students' responses on visualizing subjects on the map.

Translated transcripts (in English)	Original transcripts (in Spanish)
Male, 10th semester, three subjects	
"It really is faster and more visual to see the subjects I have pending to do. Normally, if you put them in an Excel format, it is a long list and you do not have the student record at a glance."	"Realmente es más rápido y visual ver las asignaturas que tengo pendientes por hacer. Normalmente si las pones en formato excel es una lista larga y no tienes el expediente a la vista de un vistazo."
Male, 3rd semester, two subjects	
"I can see that I have taken quite a few subjects but also that I have done a lot. (...) It is a good way to see the subjects that I have taken and that I have validated."	"Puedo ver que llevo bastantes asignaturas pero también que tengo mucho camino hecho. (...) Es una buena forma de ver las asignaturas que he hecho y que tengo convalidadas."

Nevertheless, the qualitative study identified several areas for improvement within the map visualization. Students expressed a preference for avoiding acronyms and requested a clearer representation of prerequisite relationships between subjects. Additionally, Table 6.8 highlights that some students misinterpreted the meaning of the space occupied by the subjects within the map.

Table 6.8 - Open responses (negative about the map)
Students' open responses on visualizing subjects on the map.

Translated responses (in English)	Original responses (in Spanish)
Female, 8th semester, two subjects	
"The map is a very visual way to see what you have left (...) although I find it a bit complicated."	"El mapa es una forma muy visual de ver cuánto te falta (...) aunque lo veo un poco complicado."
Male, 6th semester, one subject	
"It is very confusing for me to identify the acronyms (...) I understand that the size that has been given to the subjects is the workload. That is, in this map distributed systems will have more workload than artificial intelligence."	"Es muy confuso para mí identificar los acrónimos (...) Entiendo que el tamaño que se ha dado a las asignaturas es la carga de trabajo. Es decir, en este mapa Sistemas distribuidos llevará más carga de trabajo que Inteligencia artificial."
Male, 8th semester, two subjects	
"I understand that the region that the subjects occupy reflects their difficulty"	"Entiendo que la región que ocupan las asignaturas refleja la dificultad de las mismas"

While the student misinterpretations regarding the area occupied by subjects suggest room for improvement on the map design, it is important to acknowledge the map's overall effectiveness. Most students successfully recognized their completed, failed, and pending subjects within the visualization. This indicates that the map visualization fulfills its core purpose of providing a clear overview of the student record and their academic progress. Future iterations can benefit by incorporating student feedback, such as clearer prerequisite visualizations and avoiding acronyms, to enhance the overall usability of the prototype.

Table 6.9 - Student's preferences (about sliders)
Students' preferences regarding the slider values. Note that there were 27 participants, but some of them chose two or three factors as the most important.

Students' preferences	Mentions in interviews
Prerequisites are the most important factor	24
Difficulty is the most important factor	7
Overlaps between deadlines is the most important factor	3
Popularity is the most important factor	0

Based on the data in Table 6.9 about student weighting of subject selection factors, it is surprising to see how the prerequisites are the most important factor in most cases. This finding aligns with the idea that the map should represent prerequisites explicitly. The importance of prerequisites further emphasizes the need to explore their representation within the first visualization, a theme worth revisiting in future studies. However, subject popularity emerged as the least important factor in almost all cases. This aligns with the findings from Chapter 4 on *factors that students take into account when selecting subjects*, where *the number of students in the classroom* was found to be the least influential. Online and open education offers a unique flexible learning environment where students can advance independently, without the constraints of a traditional class structure or being enrolled in the same subjects as the rest of the students.

The number of subjects students enrolled in for the semester varied significantly, with one to three being the most popular choices. This reinforces the findings from previous chapters, suggesting students strategically select subject loads to manage their workload effectively. It is important to recall that, at the time of performing the interview, students had already enrolled and were actually taking some subjects. Therefore, the aim was to explore how students perceived the system's recommendations compared to their actual subject selections.

Opinions regarding the recommendation system were mixed, as shown in Table 6.10. Over half of the students felt the recommendations did not fully address their needs. Two key factors contributed to this, namely the itineraries and prerequisites. The itineraries represent the specialized areas students choose towards the end of their university studies. At UOC's Computer Science studies, five itineraries can be selected: Computer Science, Software engineering, Computing, Information systems and Information technologies. These itineraries are formed by selecting optional subjects. In 8 out of 14 cases that were considered not appropriate, the system suggested subjects outside the student's chosen itinerary. This is an interesting limitation, as the current learning dashboard lacks the functionality to integrate student-selected itineraries, although the popularity slide moves closer subjects that are enrolled together (often those on the same itinerary). Future studies could incorporate a feature where students can specify their chosen itinerary, addressing this crucial issue.

Table 6.10 - Students' standpoints (about the recommendations)
Students' feedback regarding the recommendation system (N=27).

Students' standpoints	Mentions in interviews
The student believes that the recommendation is appropriate	**13**
The student does not believe that the recommendation is appropriate	**14**
The recommendation system recommends elective subjects that are not from the itinerary selected by the student	**8**
The recommendation system recommends subjects in an unusual order	4
The student does not change their mind when they see the recommendation	**15**

Table 6.11 - Open responses (about itineraries)
Students' open responses on itinerary representation on the prototype.

Translated responses (in English)	Original responses (in Spanish)
Male, 6th semester, three subjects	
"I imagine that the prototype is not taking my itinerary into account (...) If it took the itinerary into account it would help more with the precision of the recommendation. Since I have few credits left, I would discard the recommended elective subjects"	"Imagino que la herramienta no está teniendo en cuenta mi itinerario (...) Si tuviese en cuenta el itinerario ayudaría más a la precisión en la recomendación. Al quedarme pocos créditos las asignaturas optativas recomendadas las descartaría"
Male, 3rd semester, two subjects	
"If the prototype knew the itinerary, I think it would be even more precise. There are itineraries in which you have to enroll in a precise way. Because if you miss a semester in a subject, then you have to wait a year to do it."	"Si la herramienta supiera el itinerario, yo creo que aún afinaría más. Hay itinerarios en los que hay que avanzar de una manera precisa. Porque si te pierdes un semestre en una asignatura, luego tienes que esperar un año para hacerla."

Student responses highlight a limitation in the proposed recommendation system: Its lack of consideration for individual subject itineraries, as shown in Table 6.11. Students feel the prototype would be more precise if their itinerary was taken into account. This is particularly important for students with few credits remaining, as irrelevant elective recommendations would be less helpful. For some programs, specific enrollment sequences are crucial and missing a required subject in one semester can cause year-long delays. These insights suggest that incorporating student itineraries into the recommendation system could significantly improve the prototype's effectiveness. Although subjects in the same itinerary are located close to each other on the map (due to the popularity criterion), it is not enough to ensure they are always selected. Therefore, as we did in the case of previously failed subjects, we could manipulate the distances between the pending subjects and the already passed subjects of a given learning itinerary. Nevertheless, the student might need to provide their preferred itinerary when using the recommendation system.

In 4 out of 14 instances where students did not find suitable recommendations, the system suggested subjects in an unconventional order (for instance, English II before English I). This particular case happens because students can take English II and, upon successful completion, receive automatic validation for English I. However, this is not the case for other recommended subjects with prerequisites. It is important to note that over half of the students had already chosen subjects that aligned with the system's recommendations. This study was conducted after students had already enrolled in their subjects. The recommendation system often suggested subjects that students had chosen for the current semester.

Table 6.12 - Open responses (positive about recommendations)
Positive opinions related to recommendations.

Translated responses (in English)	Original responses (in Spanish)
Male, 6th semester, one subject	
“This recommendation does not help me for the current semester but it does help me for the next semester. I was planning to enroll in these two recommended subjects.”	“Esta recomendación no me ayuda para el semestre actual pero sí para el siguiente semestre. Estas dos asignaturas recomendadas tenía pensado matricularlas.”
Male, 6th semester, one subject	
“The recommendation coincides with the subjects I had selected.”	“La recomendación coincide con las asignaturas que había seleccionado.”

While the map visualization and recommendation system may have room for improvement, both students and advisors agree that the calendar visualization is the most valuable feature. The calendar aligns with Shneiderman's "details on demand" mantra (Shneiderman, 2003). Once the student has selected their subjects, the calendar provides a detailed view of their schedule. All students identified the deadlines clearly displayed on the calendar, demonstrating its successful visualization of workload distribution. Furthermore, seeing their entire schedule on the calendar, including upcoming deadlines and potentially conflicting assignments, prompted most students to adjust their subject enrollment plans. This aligns with previous findings (including the questionnaire presented in Chapter 4) highlighting time management as a top student concern. Although some students appreciate the visual representation of their academic record, the calendar's functionality in managing workload has proven to be the learning dashboards' greatest strength.

As can be seen in Table 6.13, responses highlight the calendar visualization as a key functionality for managing students’ workload. By visualizing deadlines in the calendar, they can plan their schedule around their own schedule and avoid periods of heavy workload. While finding the map and recommendation system valuable, the students particularly appreciate the calendar's ability to visually represent potential scheduling conflicts.

Table 6.13 - Student's standpoints (about the calendar)
Students' standpoints regarding the calendar visualization (N=27).

Students' standpoints	Mentions in interviews
The student identifies the moment with the most deadlines	**27**
Average number of days until deadline	7.41
The calendar visualization would have made the student change their mind about the subjects to enroll in this or another semester	**23**
The calendar is the best feature in the learning dashboard	**21**
Seeing the whole degree in a visual way is the best feature in the learning dashboard	13

Table 6.14 - Open responses (about the calendar)
Students' feedback regarding the calendar visualization.

Translated responses (in English)	Original responses (in Spanish)
Male, 8th semester, two subjects	
"The calendar is very useful for me, in order to know when you are going to have deadlines and to be able to plan. I sometimes have to travel for work and if I'm away for a week, that week I'm at a conference, it's going to be difficult for me to focus. So, if I see that the dates coincide with trips or that they accumulate at one time, that makes me change my decision."	"El calendario es muy útil para mi, para saber cómo te van a caer las entregas y poder planificar. Yo por trabajo a veces tengo que viajar y si estoy una semana fuera, esa semana que estoy de congreso, me va a costar centrarme. Entonces, si veo que las fechas me cuadran con viajes o se me acumulan mucho en una época, eso me hace cambiar la decisión."
Male, 4th semester, one subject	
"The map and the recommendation system are very good. But what I liked the most is seeing the overlap that you may have between activities from different subjects and the deadlines."	"El mapa y el recomendador están muy bien. Pero lo que más me ha gustado es ver el solapamiento que puedas tener entre actividades de diferentes asignaturas y las fechas de entrega."

Furthermore, we asked students and advisors what additional functionality they would create for the learning dashboard (refer to Table 6.15). Three main functionalities derived from the responses: To specify the kind of evaluation activities, the visualization of specific prerequisite information, and subjects to be recommended not only in the next semester but further in the future. Both students and advisors highlighted the type of evaluation (for example, final exams or assignments) as the most desired. This information directly impacts their time management strategies, as the workload distribution varies depending on the evaluation type. Final exams usually take place days after the last assignments are submitted.

Table 6.15 - Desired extra functionalities
Students' ideas for additional functionalities in the learning dashboard (N=27).

Students' desired extra functionalities	Mentions in interviews
Add the type of evaluation to the calendar visualization	9
Add prerequisite information showed in UOC's official enrollment diagram	6
Add future semester recommendations	5

Nevertheless, while a clear deadline schedule is valuable, understanding the time commitment required for each subject might be challenging. Some advisors pointed this out during interviews, emphasizing that subjects with fewer activity deadlines might involve significant dedication nevertheless. Table 6.16 opinions emphasize the disconnect between the number of activities and actual subject difficulty. A higher number of activities doesn't necessarily equate to a more demanding subject. Moreover, subjects with fewer activities might require significant dedicated study time.

Table 6.16 - Open responses (about activity dedication, advisors)
Advisor feedback regarding student activity dedication.

Translated responses (in English)	Original responses (in Spanish)
Male, advisor since February 2016	
"There are times when there are many activities in a subject but they are shorter and less difficult. There are other times that there are subjects with very few activities but more difficult."	"Hay veces que hay muchas actividades en una asignatura pero son más cortas y la dificultad es menor. Hay otras veces que hay asignaturas con muy pocas actividades pero la dificultad es mayor."
Male, advisor since September 2016	
"It is true that some subjects have many assignments but those can be easy. There are other subjects that may have less assignments but you have to dedicate a lot of time to them. More activities does not mean more work, but maybe (those activities) are easier."	"Algunas asignaturas es cierto que tienen muchas entregas que pueden ser más ligeras. Hay otras que pueden tener menos pero hay que dedicarles mucho tiempo. Más cantidad de entregas no tiene por qué significar más trabajo, sino que se hacen más fácilmente."

Besides the type of activities, 6 out of 27 students asked specifically for the prerequisite information shown in UOC's official enrollment diagram (Figure 4.4). This supports the fact that prerequisites are one of the most important factors for students. Therefore, a need emerged for the learning dashboard to explicitly display prerequisite information. This aligns with the findings presented in Section 5.4.2, where the advisor evaluation also highlighted the importance of clear prerequisite visibility.

Table 6.17 - Open responses (about prerequisites)
Advisor feedback regarding the visibility of prerequisites.

Translated responses (in English)	Original responses (in Spanish)
Female, advisor since February 2010	
“The map is interesting, it captures your attention. But perhaps viewing the recommendations would help you see the journey you are taking and what you are missing, like in the UOC .pdf.”	“El mapa es interesante, llama la atención. Pero a lo mejor la visualización de las recomendaciones te ayudaría a ver el recorrido que estás haciendo y lo que te falta, como en el PDF de la UOC.”
Male, advisor since September 2016	
“In the document we have of enrollment recommendations, the subjects are grouped by theme and with arrows to see the prerequisites”	“En el documento que tenemos de recomendaciones de matrícula están las asignaturas agrupadas por temática y con flechas para ver los requisitos”

Five students expressed interest in future recommendations for their entire degree program, not just the next semester. This suggests that some students are looking to plan their time management well in advance in a full grade calendar visualization, similar to how the semester calendar visualization effectively helps them manage workload. Considering the popularity of the calendar view, exploring long-term recommendations could be an interesting avenue for future studies. If the system recommends six subjects and the student chooses three, the remaining three could be considered for future semesters. Similarly, if ten subjects are recommended and three are chosen, the other seven could potentially be recommended in the two or three future semesters. However, recommending subjects that are significantly “away” from the student's current path can lead to less guided academic journeys.

Table 6.18 - Open responses (about future recommendations)
Student feedback regarding future recommendations.

Translated responses (in English)	Original responses (in Spanish)
Male, 4th semester, one subject	
“It would be interesting if the recommendation system proposed subjects beyond the next semester. A plan for the future.”	“Sería interesante que el recomendador te propusiera asignaturas más allá del siguiente semestre. Una planificación a futuro”
Male, 7th semester, two subjects	
“A planner could be good to see what you are going to do for the next 4 semesters. A future plan to see what the timeline will be like.”	“Un planificador podría ir bien para ver qué vas a hacer los siguientes 4 semestres. Una planificación a futuro para ver cómo es la línea temporal.”

In general, advisors supported the enrollment decisions students made after using the learning dashboard. It's important to remember that advisors primarily provide guidance and feedback to students, and wouldn't typically override their choices. However, they might intervene if a student's selections significantly contradict their academic record, especially if they have not passed the prerequisite subjects.

Table 6.19 - Stakeholders' standpoints
Student and advisor standpoints on enrollment choices after using the learning dashboard (N=27)

Students' and advisors' standpoints	Mentions in interviews
The advisor agrees with the student decision about enrollment	27
The learning dashboard helps facilitates collaborative decision making	**23**

In 23 out of 27 interviews, both students and advisors indicated that the learning dashboard facilitated collaborative decision making. This is particularly interesting because advisors currently lack access to the university's subject deadline schedule, students' individual availability and, in many cases, students' validated subjects (unless students inform about it).

Table 6.20 - Open responses (about decision making)
Feedback on the impact of the learning dashboard on decision making processes.

Translated responses (in English)	Original responses (in Spanish)
Female, 5th semester, three subjects	
"I think so because it makes it easier for me to see where I am. In the case of the advisor it saves a lot of time entering the student record. With the prototype, the advisor knows better my experience in other semesters."	"Creo que sí porque me facilita ver donde estoy. En el caso del tutor le ahorra un montón de tiempo de entrar en el expediente. Con la herramienta, el tutor conoce mejor mi trabajo en otros semestres."
Male, 4th semester, six subjects	
"It seems like an ideal prototype to me. The advisor would have a much broader perspective of my career."	"Me parece una herramienta ideal. El tutor tendría una perspectiva mucho más amplia de mi trayectoria."

In conclusion, these findings revealed a positive reception for the learning dashboard across students with varying academic backgrounds. The calendar visualization emerged as a particularly valuable functionality for both students and advisors. Furthermore, both stakeholders highlighted the potential of the dashboard to facilitate collaborative decision making. Implementing the prototype within the enrollment process could equip advisors with two crucial information sources: Subject activity schedules and student-specific information regarding validated subjects and other subjects they do not wish to enroll in, besides an easier access to their academic record. This combined information, shown in the learning dashboard, has the potential to significantly improve the feedback process between advisors and students. The map visualization effectively provides an overview of student academic records, although there's room for improvement in areas like subject identification, explicit representation of subject requirements, and student understanding of the subject area size derived from its placement on the map. General prototype improvements suggested by students and their advisors might include a system of layered information on demand, explicit rules for managing subject requirements within the recommendation system, the ability for students to pre-select their preferred itinerary, and the generation of recommendations for multiple semesters (beyond just the next one). All these conclusions will be further discussed in Chapter 7.

6.5 Student final questionnaire results

This section explores students' user experience with the learning dashboard through a questionnaire, which was adapted from the Technology Acceptance Model (TAM) specifically for learning dashboard projects. While not a full or traditional application of TAM, it serves as an inquiry into four key areas of interest: Perceived ease of use, perceived usefulness, acceptance and satisfaction. Our intention was to evaluate how easy students found the dashboard to understand and navigate, how the dashboard impacted students' decision-making processes during enrollment, student interest in using the dashboard for future enrollments and an overall satisfaction rating for the enrollment experience, including the learning dashboard, and an open-ended question for additional feedback.

Table 6.21 - Student's standpoints (about ease of use)

Students' standpoints of the learning dashboard's ease of use (N=27).

Students' standpoints	Mentions in interviews
The information is easy to understand and interpret	25
The learning dashboard is easy to use	23
The map is difficult to understand	8

Students generally found the learning dashboard (Table 6.21) easy to use and understand. The information itself was clear and interpretable by a large majority (25 out of 27 interviews). Similarly, most students (23 out of 27) reported a positive experience using the prototype overall. However, a small portion of students (8 out of 27) expressed difficulty understanding the map visualization, suggesting a need for potential improvement in its design or user guidance.

Student responses on ease of use were mixed. Some found the dashboard intuitive, particularly praising the color scheme. However, others felt there was a slight learning curve, especially regarding the clarity of subject acronyms on the map visualization. This suggests that while the dashboard has a generally positive user-friendliness rating, some minor improvements to the map display could further enhance ease of use.

Table 6.22 - Open responses (about ease of use)
Qualitative feedback on the perceived ease of use of the learning dashboard.

Translated responses (in English)	Original responses (in Spanish)
Male, 8th semester, one subject	
“Yes, it is easy to use. Especially because of the choice of colors chosen to differentiate the subjects completed, those pending, etc. Also for being able to see in a general way the deadlines of the different subjects and being able to plan in advance.”	“Sí, sobre todo por la elección de colores elegidos para diferenciar las asignaturas realizadas, de las pendientes, etc. También por poder ver de manera general las entregas de las diferentes asignaturas y poder planificar de antemano.”
Male, 4th semester, four subjects	
“It is easy to use, in addition to being very visual, which helps to receive information more clearly and without using as much time as is currently required.”	“Es sencilla de utilizar, además de ser muy visual, lo que ayuda a la hora de que se reciba la información de manera más clara y sin utilizar tanto tiempo como se requiere actualmente.”
Male, 6th semester, one subject	
“A priori it is not easy to understand, it has a small learning curve. Once familiar with the prototype, you can proceed fluently. Furthermore, on the subject map the names of the subjects are not shown clearly.”	“A priori no es fácil de entender, tiene una pequeña curva de aprendizaje. Una vez familiarizado con la herramienta, se puede proceder con fluidez. Además en el mapa de asignaturas los nombres de las mismas no se muestran con claridad.”

Students mostly found the learning dashboard to be a valuable prototype for making decisions about their enrollment (26 out of 27 interviews) as can be seen in Table 6.23. Many students (16 out of 27) felt the recommendations the prototype provided were helpful. However, some students (6 out of 27) suggested the learning dashboard could be improved by placing a greater emphasis on prerequisite subject requirements when making recommendations. Additionally, a smaller group (4 out of 27) thought the recommendations would be even better if they considered students' chosen itineraries. This suggests that future iterations could focus on incorporating prerequisites and potential pathways into the recommendation system for a more personalized experience, taking into account student records and their itinerary preferences.

Table 6.23 - Students’ standpoints (about effectiveness)
Students' standpoints on the effectiveness of the prototype in supporting decision making (N=27).

Students’ standpoints	Mentions in interviews
The learning dashboard improves or facilitates the decision-making process	26
The learning dashboard makes appropriate recommendations	16
The recommendation system can be improved taking into account prerequisites	6
The recommendation system can be improved taking into account the students' itinerary	4

Student responses on the decision-making usefulness of the learning dashboard were overwhelmingly positive. Many students appreciated the ability to combine the map visualization with the deadline calendar, providing a comprehensive view of subject offerings and deadlines not previously available. The prototype's functionalities, such as recommendations and the ability to visualize subject overlaps, were seen as valuable aids in subject selection. However, one student highlighted a limitation - the lack of a clear visual representation of prerequisite dependencies, suggesting a potential area for improvement.

Table 6.24 - Open responses (about impact)
Qualitative feedback on the impact of the learning dashboard on decision-making processes.

Translated responses (in English)	Original responses (in Spanish)
Male, 10th semester, three subjects	
“Yes. It allows you to easily make combinations with the subject map and adds the functionality of the deadline calendar, which is currently unavailable information.”	“Sí. Te permite ir haciendo combinaciones fácilmente con el mapa de asignaturas y añade la funcionalidad del calendario de entregas, que es información no pública actualmente.”
Male, 7th semester, two subjects	
“Yes, since being able to consider things like recommendations based on the priority of your criteria or seeing the overlap between subjects helps you decide which subjects to take.”	“Sí, ya que al poder considerar cosas como recomendaciones en base a la prioridad de tus criterios o ver el solapamiento entre asignaturas ayuda a decidir qué asignaturas tomar.”
Male, 4th semester, six subjects	
“Before submitting the enrollment proposal, I think we all look for a way to make a justified selection based on our circumstances. In that sense, it helps greatly since a large part of the criteria we use are developed in this prototype.”	“Antes de presentar la propuesta de matrícula, creo que todos buscamos una forma de hacer una selección de forma justificada con arreglo a nuestras circunstancias. En ese sentido, ayuda en gran medida ya que gran parte de los criterios que utilizamos, están desarrollados en esta herramienta.”
Male, 8th semester, two subjects	
“Not for me, because the dependency between subjects (prerequisites) needs to be made more visual.”	“Para mi no, porque falta hacer más visual la dependencia entre asignaturas.”

Student feedback regarding the recommendation system's accuracy was mixed. Some found the suggestions aligned with their initial subject selections. However, others identified several limitations. On the one hand, the system does not allow students to further customize the recommendation system by adding the itinerary or preferred subject order. On the other hand, the lack of a strong prerequisite filtering resulted in suggestions that wouldn't be possible due to subject prerequisites.

Table 6.25 - Open responses (about accuracy and relevance)
Qualitative feedback on the accuracy and relevance of recommendations provided by the learning dashboard.

Translated responses (in English)	Original responses (in Spanish)
Male, 8th semester, two subjects	
"Yes, it makes appropriate recommendations. The prototype makes proposals in accordance with the premises introduced."	"Sí. Realiza propuestas acordes a las premisas introducidas."
Male, 7th semester, one subject	
"In my case, the recommendation was not correct because there are things that the system cannot know (that I want to leave English for the end, that I may have subjects pending validation processes...) Furthermore, in the last years, some subjects are linked to a semester, and since many have a recommended order, I have planned the next subjects in advance (my case is special, as I do one subject per semester)"	"En mi caso no ha acertado la recomendación porque hay cosas que no puede saber el proceso (que me quiero dejar inglés para el final, que puedo tener asignaturas pendientes de procesos de convalidación...) Además, en últimos cursos, algunas asignaturas están ligadas a un semestre, y como muchas tienen un orden recomendado, yo tengo planificado los próximos cursos por adelantado (mi caso es especial, una asignatura por semestre)"
Male, 3rd semester, two subjects	
Yes, although more criteria need to be processed. Taking into account that it does not filter by itinerary and does not have an order of preference for subjects (from what I understood), it did offer one of those that I am currently taking and another that could potentially be taken. An important issue was the order of preference: It offered English II when it was required to pass I previously.	Sí, aunque le falta procesar más criterios. Teniendo en cuenta que no filtra por itinerario y no dispone de orden de preferencia de asignaturas (por lo que entendí), sí que ofreció una de las que actualmente estoy cursando y otra potencialmente cursable. Un tema importante era el orden de preferencia: Ofreció Inglés II cuando se requiere superar la I previamente.

As for the acceptance of the prototype by students, all participants (27 out of 27) expressed their intention to use it for the next enrollment period. Student responses regarding future use of the learning dashboard were generally positive. While some students expressed a desire to maintain control over subject selection (opting for the calendar view but not relying solely on the recommendation system), many saw the prototype as a valuable aid. Students appreciated the simplification of the subject selection process, particularly the ability to consolidate information and avoid confusion compared to using personal spreadsheets. The calendar visualization was a popular feature, aiding in visualizing deadlines and workload.

Table 6.26 - Students' standpoints (about acceptance)
Student acceptance of the learning dashboard, including their intention to use it again and their preference for ongoing advisor support (N=27).

Students' standpoints	Mentions in interviews
I would use the learning dashboard for the next enrollment	27
I would continue contacting the advisor even if the learning dashboard was available	22
Average grade of the enrollment process using the learning dashboard	8,23 / 10

Table 6.27 - Open responses (about usage intentions)
Qualitative feedback on students' intentions regarding future use of the learning dashboard.

Translated responses (in English)	Original responses (in Spanish)
Male, 8th semester, three subjects	
“Yes, it helps clarify ideas and it is no longer necessary to use your own Excel with all the possible variables. It simplifies (the enrollment process) and helps not having to get lost in so much information.”	“Si, ayuda a clarificar ideas y ya no es necesario usar Excel propios con toda la cantidad de variables posibles. Simplifica y ayuda el no tener que perderse en tanta información.”
Female, 8th semester, two subjects	
“The calendar visualization, yes. The subject recommendation system no. I would decide for myself which subjects to choose and verify the deadlines with the prototype”	“La visualización de las fechas de entrega si. El recomendador de asignaturas no. Decidiría por mí misma qué asignaturas escoger y verificaría las entregas con la herramienta”
Male, 7th semester, one subject	
“Of course, yes. I always hesitate between doing one or two subjects. It can help me in the decision process”	“Desde luego, sí. Siempre dudo entre hacer una o dos asignaturas. Me puede ayudar en el proceso de decisión”

Interestingly, even with the prototype available, a strong majority (22 out of 27) still wanted to consult with their advisors, suggesting the importance of advisor’s feedback. This answers one of the key questions when evaluating the learning dashboards and proves that tools can not replace human interactions in some cases, especially in the advising process. Most students appreciated the advisor's role as essential for final subject selection and felt that human oversight remained crucial in the enrollment process. Other students perceive the learning dashboard as a valuable pre-consultation resource, facilitating communication and decision making with their advisor by providing a starting point for discussions about subject selection. Interestingly, a small minority felt the prototype's automated recommendations made advisor contact unnecessary. These mixed responses suggest the learning dashboard may not entirely replace advisor interactions, but rather serve as a complementary tool to enhance the advising process.

Overall satisfaction with the learning dashboard was high, with students giving the enrollment process including the prototype an average rating of 8,23 out of 10. This outranks the average grade on the registration process without the prototype, which had a score of 7,63. These results suggest the prototype has promise for improving the student enrollment experience.

Table 6.28 - Open responses (about advisor consultation)
Qualitative feedback on students' preferences for advisor consultation, even with access to the learning dashboard.

Translated responses (in English)	Original responses (in Spanish)
Male, 6th semester, one subject	
“Of course I would continue to contact them since the advisor has the final say in choosing subjects. In addition, the registration process must have the supervision of a human.”	“Por supuesto que lo seguiría contactando puesto que tiene la última palabra en cuanto a elegir asignaturas. Además el proceso de matriculación debe contar con la supervisión de un responsable humano.”
Male, 3rd semester, two subjects	
“Yes, although I would do it regardless of the prototype. The UOC has a very adequate advising program to guide you on your academic path and having a person experienced in this task allows for better guidance. In fact, its result is an added value to advising. Obviously, I would contact my advisor using the results of the prototype to facilitate communication and decision making about the subjects to enroll in the next semester.”	“Sí, aunque lo haría independientemente de la herramienta. La UOC tiene un seguimiento de tutoría muy adecuado para orientarte en tu camino académico y tener una persona experimentada en esta tarea permite una mejor orientación. De hecho, su resultado es un valor añadido a la tutoría. Obviamente, contactaría con mi tutora usando los resultados de la herramienta para facilitar la comunicación y la toma de decisión de las asignaturas a matricular en el próximo semestre.”
Male, 4th semester, six subjects	
“Yes, I believe that a prototype should serve as a help when deciding, but it should not replace the knowledge and experience of an advisor. In general, I believe that the complex circumstances behind each student at this University require the availability of a person who can ultimately help you in the selection process, although sometimes it is not necessary.”	“Sí, creo que una herramienta debe cumplir una función de ayuda a la hora de decidir, pero no debe sustituir los conocimientos y la experiencia de un tutor. En general, creo que las circunstancias complejas que hay detrás de cada estudiante en esta Universidad, requieren la disponibilidad de una persona, que en última instancia, pueda ayudarte en el proceso de selección, aunque en ocasiones no sea necesario.”
Male, 6th semester, three subjects	
I would not contact the advisor (...) since the prototype already makes an automatic proposal of subjects.	En principio no (...) ya que la herramienta ya te realiza una propuesta automática de asignaturas.

Finally, questionnaire data (Table 6.29) highlights clear preferences for specific learning dashboard features. The calendar visualization emerged as the most popular feature, with 22 out of 27 students mentioning its value in interviews. The map visualization, while interesting to 12 students, was less popular than the calendar in terms of mentions. The slider functionality garnered the least interest, with only 3 students highlighting it during the interviews. These findings suggest that the calendar visualization should be a core focus for future development efforts.

Table 6.29 - Preferred features
Preferred features of the learning dashboard (N=27).

Dashboard design preferred features	Mentions in interviews
The calendar visualization is the most interesting feature	22
The map visualization is the most interesting feature	12
The sliders are the most interesting feature	3

Table 6.30 - Open responses (about preferred features)
Qualitative feedback on the preferred features of the learning dashboard.

Translated responses (in English)	Original responses (in Spanish)
Male, 7th semester, two subjects	
“The calendar of activities with the overlap between the chosen subjects.”	“El calendario de actividades con el solapamiento entre las asignaturas escogidas.”
Male, 4th semester, six subjects	
“I think they are all relevant, although having the calendar and workloads distributed on a timeline are really essential.”	“Creo que todas son relevantes, si bien contar con el calendario y las cargas de trabajo distribuidas en una línea temporal son realmente imprescindibles.”

In conclusion, this last student questionnaire evaluating the learning dashboard prototype indicates strong potential for its role in improving UOC's enrollment experience. Students found the dashboard easy to understand and a valuable decision-making aid. While the recommendation system garnered positive feedback, suggestions for incorporating prerequisite emphasis and student itineraries offer valuable directions for future development. Interestingly, despite the prototype's positive reception, students still valued advisor consultations, suggesting the dashboard complements rather than replaces human interaction. High overall satisfaction ratings and student preference for the calendar visualization further strengthen the case for the learning dashboard's potential. By addressing improvement suggestions and focusing on preferred features, future iterations can solidify the learning dashboard as a valuable prototype for both students and advisors.

6.6 Advisor questionnaire results

This section explores advisor perceptions of the learning dashboard through a questionnaire. The questions mirrored those in the student final questionnaire with a focus on key areas relevant to the advisor role: Experiences with information clarity and overall user-friendliness, the impact of the dashboard on decision making and the accuracy of the recommendation system, advisor’s interest in utilizing the dashboard for future enrollments and identifying the features they found most valuable. Furthermore, advisors were asked about the potential for proactive advising using the learning dashboard.

Table 6.31 - Advisors' standpoints (about ease of use)
Advisors' standpoints on the learning dashboard's ease of use (N=9).

Advisors' standpoints	Mentions in questionnaire
The information is easy to understand and interpret	6
The learning dashboard is easy to use	9

Table 6.32 - Open responses (about ease of use, advisors)
Advisors' feedback on the ease of use of the learning dashboard.

Translated responses (in English)	Original responses (in Spanish)
Male, advisor since September 2010	
"Yes, it seems simple and usable to me. Perhaps the least intuitive thing is the subject map, you cannot see the progress and the names of the subjects at a quick glance"	"Sí me parece sencilla y usable. Quizá lo menos intuitivo es el mapa de asignaturas, no se ve de un vistazo rápido el progreso y el nombre de las asignaturas"
Male, advisor since February 2010	
"It is easy to understand thanks to the visualization. You quickly see where you are in the case of the subject map and the workload in the deadline calendar."	"Es fácil de entender gracias a los gráficos. Visualmente se ve rápidamente dónde estás en el caso del mapa de asignaturas y la carga de trabajo en el calendario de entregas."
Female, advisor since February 2010	
"I find it easy to use and to advance through the different contents"	"Me parece fácil de utilizar y de avanzar en los diferentes contenidos"

An analysis of advisors' standpoints on perceived ease of use (Table 6.31) reveals positive perceptions of the learning dashboard. The majority of advisors (6 out of 9) found the information clear and interpretable, and all advisors (9 out of 9) reported that the dashboard itself was easy to use. Advisors generally found the learning dashboard easy to use, highlighting the clarity of visualizations. The calendar view provided a quick snapshot of workload, and the map helped visualize progress through the program. While a few advisors found the subject map slightly less intuitive regarding subject names and progress tracking, overall impressions leaned towards a user-friendly experience.

While most advisors found the learning dashboard easy to use, some expressed concerns about the map visualization. The subject map, particularly its ability to display progress and subject names clearly, caused some confusion. Additionally, one advisor found the initial interpretation of the bars representing deadline dates on the calendar visualization to be unclear.

Table 6.33 - Open responses (about challenges, advisors)
Advisors' feedback on any challenges encountered in interpreting information from the learning dashboard.

Translated responses (in English)	Original responses (in Spanish)
Female, advisor since February 2010	
"The map visualization is not very intuitive"	"La visualización del mapa no es muy intuitiva"
Male, advisor since February 2010	
"Perhaps the map (visualization) that shows the subjects already taken and those that remain to be taken can be a little confusing at first. (...) Nevertheless, regarding the graph where you see the deadlines of each subject, perhaps at first you cannot understand the bars that appear the days before a deadline."	"Quizás el mapa (gráfico) que muestra las asignaturas ya cursadas y las que quedan por cursar puede resultar un poco confuso al principio. (...) Por otro lado, por lo que refiere al gráfico donde se ven las entregas de cada asignatura, quizás al principio no se puede entender las barras que aparecen los días previos a una entrega."

While most advisors (8 out of 9) found the learning dashboard useful for decision making, only a small portion (2 out of 9) felt the recommendation system consistently made appropriate suggestions (Table 6.34). Advisors generally acknowledged the potential of the learning dashboard to improve decision making, particularly by considering student priorities. However, several limitations were identified. A strong majority (7 out of 9) saw potential for improvement by incorporating prerequisite subject requirements into the recommendation algorithm. Additionally, several advisors (2 out of 9) suggested that considering a student's chosen itinerary could further enhance the recommendation system's effectiveness.

Table 6.34 - Advisors' standpoints (about effectiveness)
Advisors' standpoints on the effectiveness of the prototype in supporting decision making (N=9).

Advisors' standpoints	Mentions in questionnaire
The learning dashboard improves or facilitates the decision-making process	8
The learning dashboard makes appropriate recommendations	2
The recommendation system can be improved by taking into account prerequisites	7
The recommendation system can be improved by taking into account the students' itinerary	2

The lack of consideration for prerequisites within the recommendation system led to subject suggestions that should not be taken due to prior subject requirements. Additionally, the system's inability to factor in chosen itineraries resulted in recommendations that might not be relevant for students nearing graduation who have already fulfilled their elective requirements. These insights align with previous data, that incorporating prerequisites and student itineraries into the recommendation algorithm could significantly enhance the prototype's usefulness.

Table 6.35 - Open responses (about usefulness, advisors)
Qualitative feedback on the perceived usefulness of the learning dashboard.

Translated responses (in English)	Original responses (in Spanish)
Male, advisor since September 2010	
“Yes, it facilitates decision making since it takes into account the priorities of the students, with their different choices.”	“Si, facilita la toma de decisiones ya que tiene en cuenta la prioridad del alumnado, con las distintas variantes.”
Female, advisor since February 2010	
“If the prototype takes into account all the prerequisites so that a subject can be taken, it could be very useful.”	“Si la herramienta llega a contemplar todos los requisitos para que se pueda cursar una asignatura, podrá llegar a ser de mucha utilidad.”
Male, advisor since February 2010	
“Right now it does not make the appropriate recommendations (...) the prototype recommended subjects that imply having other previous subjects - prerequisites - previously approved but that the student had not passed.”	“Ahora mismo no realiza las recomendaciones adecuadas (...) la herramienta recomendaba asignaturas que implican tener otras asignaturas previas -prerrequisitos- aprobadas previamente pero que el estudiante no tenía superadas.”
Male, advisor since September 2010	
“In general yes, although it needs to be refined taking into account the chosen itinerary. For example, it makes no sense to recommend electives that are not part of the itinerary if you already have the full elective credits.”	“En general sí, aunque le falta afinar teniendo en cuenta el itinerario escogido. No tiene sentido por ejemplo aconsejar optativas que no sean del itinerario si ya se tiene los créditos de optativas completos.”

Regarding acceptance, all advisors (8 out of 9) expressed an intention to use the prototype for future enrollments (Table 6.36). Advisor responses regarding future use of the learning dashboard were cautiously optimistic. While some advisors expressed a desire to wait for further refinement, particularly in regards to the recommendation system, others saw its current capabilities as valuable for improving the advising process. Some advisors believe the prototype can facilitate decision-making discussions and improve communication with students, especially those in earlier semesters who might require more guidance.

Table 6.36 - Advisors’ standpoints (about acceptance)
Advisors’ standpoints on the learning dashboard acceptance (N=9).

Advisors’ standpoints	**Mentions in questionnaire**
I would use the learning dashboard for the next enrollment	8
I could make an enrollment proposal by using the learning dashboard before the student sends their selected subjects for the next enrollment	5
Average grade of the enrollment process using the learning dashboard	7,23 / 10

Table 6.37 - Open responses (about future use, advisors)
Qualitative feedback on advisors' intentions regarding future use of the learning dashboard.

Translated responses (in English)	Original responses (in Spanish)
Female, advisor since February 2010	
“I would not use it yet, since it is not refined so that it proposes the recommended subjects, which is what I rely on as an advisor to validate an enrollment proposal”	“Todavía no la utilizaría, puesto que no está depurada para que proponga las asignaturas recomendadas, que es en lo que me baso como tutora para validar una propuesta de matrícula”
Male, advisor since September 2010	
“Yes, I would use the prototype since it helps in decision making and in the relationship with the student, especially those who have records that are not excessively advanced.”	“Si utilizaría la herramienta ya que ayuda en la toma de decisiones y en la relación con el alumno, especialmente los que tienen expedientes no excesivamente avanzados.”
Male, advisor since February 2010	
"Yes. I am convinced that advising would go faster and the student would also see more easily the reason for making one suggestion or another. In fact, I am convinced that there would be an improvement in the enrollment proposals.”	“Sí. Estoy convencido de que iría más rápido tutorizando y el estudiante también vería más fácilmente el porqué de hacer una sugerencia u otra. De hecho estoy convencido de que habría una mejora en las propuestas de matrícula de los estudiantes.”

Table 6.38 - Open responses (about the process, advisors)
Qualitative feedback related to making an enrollment proposal by using the learning dashboard before the student sends their selected subjects.

Translated responses (in English)	Original responses (in Spanish)
Male, advisor since February 2010	
“The usual process is that it is precisely the student who makes an enrollment proposal and then the advisor reviews it (recommends the enrollment or not), depending on various variables. In this sense, the prototype could be used to compare whether the proposal it makes coincides with that of the student and that of the advisor. (...)”	“El proceso habitual consiste en que es precisamente el estudiante quien realiza una propuesta de matrícula y luego el tutor la revisa (recomienda o no), en función de diversas variables. En este sentido, la herramienta podría servir para comparar si la propuesta que fabrica coincide con la del estudiante y la del tutor. (...)”
Female, advisor since September 2012	
“Yes, I could make an enrollment proposal and then work on it with the student, depending on their availability and interests. (...)”	“Sí, podría hacer una propuesta de matrícula y después trabajarla con el estudiante, en función de su disponibilidad y de sus intereses. (...)”
Female, advisor since February 2010	
“No, only the student knows how they will have the following semester in terms of work or personal life and how they want to organize themselves.”	“No, solo el estudiante sabe cómo tendrá el semestre siguiente en cuanto a trabajo o vida personal y cómo se quiere organizar.”

Interestingly, over half (5 out of 9) saw the potential for proactive advising if the dashboard was available. Some advisors pictured using the prototype to compare student and advisor proposals for a more collaborative approach. Others saw potential in creating proposals for students to later review and discuss them. However, some advisors cautioned that student preferences regarding workload and personal commitments are crucial factors that the prototype cannot currently account for. These responses suggest that while the proactive proposal feature may not be universally applicable, it has the potential to enhance the advising process by providing a starting point for discussion and collaboration. This is a key finding in this research, as it suggests the potential for the prototype to transform the advising process by maybe enabling a more proactive approach.

An analysis of the desired dashboard features reveals a clear preference for the calendar visualization as the most valuable feature. All advisors (9 out of 9) found the calendar visualization interesting, compared to 4 out of 9 for the map visualization and only 2 out of 9 for the sliders feature. This suggests that prioritizing the calendar visualization in future development efforts would align with advisor preferences and mirrors the results from the student final questionnaire results.

Table 6.39 - Advisors' preferred features
Most popular dashboard design features among advisors (N=9).

Advisors' desired dashboard design features	Mentions in questionnaire
The calendar visualization is the most interesting feature	9
The map visualization is the most interesting feature	4
The sliders are the most interesting feature	2

Table 6.40 - Open responses (preferred features, advisors)
Qualitative feedback on advisors' preferred dashboard design features.

Translated responses (in English)	Original responses (in Spanish)
Female, advisor since February 2010	
"I found the calendar visualization and overlapping activities very interesting. This prototype works perfectly and could be implemented in the student profile so that they can assess the enrollment workload."	"Me ha parecido interesantísima la parte del calendario y solapamiento de actividades. Esta herramienta funciona a la perfección y se podría implementar en el perfil de los estudiantes para que puedan valorar la carga de la matrícula."
Female, advisor since September 2012	
"The map and calendar of activities, the fact of having deadline dates before the start of the semester, allows the student (that normally is also a worker) to better organize their time and avoid weeks of excess work."	"El mapa y el calendario de actividades, el hecho de tener las fechas de entrega antes de iniciar el semestre, permite al estudiante/trabajador organizar mejor su tiempo y evitar semanas de exceso de trabajo."

In conclusion, this advisor questionnaire explored advisor experiences with the learning dashboard. Overall, advisors found the prototype easy to use and helpful for decision making. However, some suggestions for improvement emerged:

- **Recommendation System:** While some advisors saw potential in the recommendation system, most felt it needed refinement. Incorporating prerequisite subject requirements and student itineraries were seen as key areas for improvement.
- **Proactive Advising:** Advisors expressed interest in proactive advising by using the learning dashboard. Some envisioned using it to generate initial subject proposals for student review and discussion. However, some cautioned that student preferences for workload and personal commitments are crucial factors that the prototype doesn't currently consider.
- **Visualization Preferences:** The calendar visualization emerged as the most preferred feature, followed by the map and sliders. This aligns with student preferences.

These findings suggest that the learning dashboard has the potential to be a valuable prototype for advisors, but further development is needed to improve the recommendation system and explore the feasibility of proactive advising features. Focusing on calendar visualization enhancements aligns with both advisor and student preferences.

6.7 Heuristics

After conducting a comprehensive investigation into the student enrollment process, which included questionnaires, interviews, and data analysis, we identified valuable insights into student needs and challenges. However, to further refine our understanding and ensure the effectiveness of a proposed enrollment decision-making prototype, we opted to conduct a heuristics study with a group of experts. By systematically evaluating the prototype through established design principles, we aim to identify potential shortcomings and areas for optimization before widespread implementation. This additional layer of evaluation will contribute to the development of a more user-friendly and effective prototype based on the specific needs of students and advisors. Despite our aim to involve four UX experts, only two were able to participate in the questionnaire due to time constraints. To facilitate their participation, an explanatory video was created, and a questionnaire based on Nielsen's heuristic evaluation principles (Nielsen, 2024) was sent along with a link to access the prototype (Annex A.5.7). The ten general usability heuristics evaluated were:

1. Visibility of system status
2. Match between the system and the real world
3. User control and freedom
4. Consistency and standards
5. Error prevention
6. Recognition rather than recall
7. Flexibility and efficiency of use
8. Aesthetic and minimalist design

9. Help users recognize, diagnose, and recover from errors
10. Help and documentation

The feedback regarding the *visibility of system status* was largely positive, indicating that the prototype had clear headings, visual indicators for menu options, and selecting and already selected options. However, the experts suggested specific improvements. One of them proposed a more prominent title to enhance visibility. Additionally, the other implied that consistent formatting should be applied to all subtitles. Both experts indicated that the subject recommendation system section could benefit from clearer visual cues to guide users through the available actions and the relationship between different elements. One expert advised to use arrows or breadcrumbs and the other indicated that the system should provide clear indications of the actions that can be performed on the map, improving user understanding and interaction.

Moreover, the experts positively evaluated the *match between the system and the real world*, especially the prototype's general color scheme and the use of familiar terminology to describe tasks. Nevertheless, the experts identified some details to improve. Regarding color coding, one expert suggested that the red/blue color scheme for indicating passed and pending statuses may not be the most intuitive choice. A more conventional red/green scheme might be more easily understood. The second expert indicated that colors should be consistent in all the process, arguing that green should not be changed to dark blue when selecting the subject. Nevertheless, green was used to indicate recommendations and the color scheme was very well received by students and advisors in the previous study. Additionally, the expert recommended simplifying the instructions on the left panel to improve readability.

The *user control and freedom* section was generally well-received. The experts highlighted that there was no need for an undo function, given the non-critical nature of actions and the lack of time-sensitive tasks. Additionally, they noted that the system's reconfigurability eliminates the need for a mechanism to return to previous actions. Nevertheless, one of the experts argued that a symbol or icon was needed to reinforce the “back” functionality and insisted on adding breadcrumbs so the user can select the step to change.

Regarding *consistency and standards*, one of the experts noted the careful use of call-to-action techniques and the provision of a legend for complex color-coded information. However, the other expert found the call-to-action techniques too homogeneous in general and expressed that some of the indications or navigation options could be emphasized more. The consistent use of terminology for user actions was in fact appreciated by both experts. Conversely, one expert identified a discrepancy between the menu structure and the actual task flow. While the overall design was correct, the persistent left panel, which is primarily used for transforming the map visualization, was seen as a potential source of confusion. As a suggested improvement, the expert recommended displaying the left panel only when necessary, such as within the recommendation system tab. The second expert also noted that in Firefox, Chrome and Opera, the floating boxes of detailed subject information were not displayed on the screen when rolling over, and were positioned to the right. This might require more testing work to improve responsiveness.

Regarding *error prevention*, experts noted the logical, distinct, and mutually exclusive nature of the menu options. The prototype was also designed trying to minimize the user errors.

Regarding *recognition rather than recall*, one expert noted the strategic placement of indications and messages within the user interface. The visual design elements, such as margins, spacing, color coding, and font usage, were considered effective in enhancing clarity and readability. The second expert agreed but recalled improvements suggested previously and added that conceptually, the principle of distance between subjects was not sufficiently clear. This feedback coincides with the tests previously carried out with students and advisors.

Additionally, when taking into account *flexibility and efficiency of use*, experts noted that the tool allows users to customize their experience. However, the level of detail provided is not adaptive to different user expertise levels. Additionally, while the data is personalized based on user selections, the overall interface remains static.

As for *aesthetic and minimalist design*, the experts noted the use of concise, clear, and distinctive titles for each data entry screen. The affirmative and active voice used in the instructions was also appreciated. Nevertheless, one expert argued that while the menu titles were considered appropriately brief and informative, the text in the left panel was found to be overly lengthy and complex.

With reference to *help users recognize, diagnose, and recover from errors*, both experts noted the constructive nature of error messages, which avoid explicit criticism of the user. The system's prompts empower users by conveying a sense of control. Additionally, the use of concise and unambiguous messages further enhances user control over the system.

Finally, regarding *help and documentation*, experts noted the clear and sequential presentation of instructions and the consistency of the help prototype's interface with the main application. In terms of navigation, the information was considered easy to locate. Furthermore, according to experts, the tool is well designed and the information it provides is relevant. While the prototype's functionality became apparent with use, one expert suggested that initial clarity could be improved. The addition of brief introductory instructions on the first screen could help alleviate this. Moreover, both experts recommended exploring ways to provide additional explanatory information for ambiguous menu options, potentially through tooltips.

In conclusion, the heuristic study highlighted several positive aspects of the prototype's design. The clear and intuitive interface, with its well-organized headings, visual indicators, and the consistent color scheme, was particularly well-received. Experts appreciated the logical flow of the interface and the ease of navigation. Additionally, they acknowledged the effectiveness of the learning dashboard in providing a customizable experience and relevant suggestions. The prototype's ability to guide users through the enrollment process and provide clear information was also commended. However, several areas for improvement were identified, such as enhancing the clarity of the subject recommendation system, improving the consistency of color usage and simplifying instructional text. The experts also suggested refining the user interface to improve the visibility of key elements and the overall user experience. While the prototype's core functionality was deemed effective, further refinements are necessary to optimize its usability and user satisfaction. The most relevant insights have been identified and will be analyzed in greater detail in Chapter 7.

6.8 Summary

This chapter describes the validation of the developed prototype: An enrollment dashboard to enhance decision making for students and advisors. It details the research design, data collection techniques and analysis procedures. The study involved students and advisors from the UOC Computer Science program. Data was collected through questionnaires, interviews, and a heuristic evaluation. The analysis of this data aimed to assess the prototype's impact on student and advisor decision making, identify areas for improvement and ultimately evaluate its potential to enhance the enrollment process.

The validation highlighted that the prototype had a positive impact on both stakeholders: students and their advisors. On the one hand, students thought that the dashboard provided a clear visual representation of their academic progress, highlighting validated, passed and pending subjects and potential enrollment subject combinations. The recommendation system offered personalized suggestions, guiding students towards suitable subject choices based on their individual needs and goals. This personalized approach empowered students to make more informed decisions. Moreover, the information provided within the map visualization was considered essential in the decision-making process. On the other hand, from an advisor's perspective, the dashboard offered valuable insights into student progress and potential challenges. It enabled advisors to identify student needs and goals. Additionally, the dashboard facilitated a more efficient and effective advising process, as some advisors could quickly assess students' academic situations and could provide tailored recommendations, even without being contacted by students beforehand. The most remarkable finding is perhaps that the majority of stakeholders thought that the learning dashboard improved or facilitated the decision-making process. Overall, the integration of a learning dashboard with a recommendation system into the enrollment process has the potential to enhance student satisfaction, improve academic outcomes and enhance the advising process.

The heuristics evaluation revealed several strengths, including a clear and intuitive interface of the learning dashboard, effective organization of information and a well-designed recommendation system. However, some details for improvement were also identified, such as enhancing the clarity of subject recommendation, refining the overall design and UX, and simplifying instructional text.

Hence, the overall evaluation of the prototype demonstrated its effectiveness but also identified some areas for improvement:

- **Map Visualization:** The current map visualization could benefit from clearer labeling and additional information layers to enhance clarity and understanding.

- **Recommendation System:** The recommendation system could be further refined by incorporating additional factors, such as student preferences and long-term academic goals.
- **User Interface:** Minor improvements to the user interface, such as enhancing the visibility of certain elements and refining the layout, could further enhance the user experience.

In the next chapter we will resume the key findings and the analysis of the prototype's strengths and limitations along with its potential opportunities for future development.

Chapter 7
Conclusions

This chapter includes a review of the research questions with a discussion of the key findings. It explores potential opportunities for future development, such as enhancing the prototype's functionality and expanding its application to different educational contexts. Additionally, the chapter reflects on the overall impact of the research and its academic implications.

As aforementioned, online education has allowed students to tailor their academic journeys to their individual needs. By offering flexibility in terms of pace and allowing for student-driven decision making, these modalities have changed traditional education models. While the flexibility of distance learning offers significant advantages, challenges such as enrollment errors, low performance and dropout can affect student success. Enrollment in open and online universities is an essential learning process where students must balance their academic aspirations with their personal and professional responsibilities. A review of the literature reveals several limitations in existing research on learning dashboards and recommendation systems in such processes. While there are numerous examples of recommendation systems applied to subject selection, few integrate them into learning dashboards and apply data visualization. Furthermore, there is a need for defining meaningful learning outcomes and creating visualizations that are both effective and accessible to students and other stakeholders. Additionally, only a few studies properly validate the impact of these learning dashboards in educational settings.

The prototype presented in this research has been designed taking into account information that is key to assist students and advisors in their enrollment decision-making processes. In order to do so, this research investigated the potential of learning dashboards to enhance student decision making during the enrollment process in higher education. More specifically, in an open and online university. Firstly, we identified key factors influencing student choices, such as academic prerequisites, personal goals and time constraints. Secondly, we developed a prototype learning dashboard to visualize this information taking into account user preferences. Finally, the effectiveness of the dashboard in supporting informed decision making was assessed through a validation process involving student and advisor interviews, questionnaires and heuristic evaluations. This research contributes to the understanding of student information needs and the role of technology in supporting the enrollment process in open universities.

7.1 Results

The findings of this research contribute valuable insights towards a comprehensive understanding of student enrollment behavior and can inform future initiatives aimed at optimizing the enrollment process at the UOC and other open and online universities. The main contributions of this thesis are:

- Identifying key enrollment factors
- Effective information visualization
- Evaluating learning dashboards and recommendation systems

We will begin by addressing the first research question, RQ1: *Which information is key for students when taking enrollment decisions in higher education official degrees that allow some flexibility?* We have carefully studied the UOC enrollment process, examining its distinct phases, the information sources students utilize and any unique aspects specific to the UOC. To gain a comprehensive understanding of student behavior, two complementary investigations were employed: a quantitative web analysis and a qualitative questionnaire. While the web analysis provided valuable insights into user activity patterns, it was limited in its ability to explore the underlying motivations behind these behaviors. The questionnaire, on the other hand, allowed us to find out more about students' information needs and preferences.

Informed by the previous analysis, we can address the first research objective of this thesis, that is, identifying key factors that can enhance students' decision-making process during enrollment. The following factors emerged as crucial for enhancing students' decision making during enrollment:

- Time available for studying
- Student experience in previous semesters
- Validated subjects
- Subject prerequisites
- Subject difficulty
- Deadline schedule overlaps between subjects
- Subject popularity

Based on these results, we summarized the academic information essential to the enrollment process, constituting the first contribution of this research: A mapping of pertinent academic information for the enrollment procedure. Time available for studies emerged as a primary factor influencing student choices, followed by their experience with subjects in their last semester. Therefore, including passed, failed and pending subjects into a learning dashboard prototype could help students better manage their time. Furthermore, the availability of activity and test schedules is a key element in designing the learning dashboard. Time management is also impacted by the number of subjects enrolled in. A subject learning dashboard should consider this by discouraging students, particularly in their first semesters, from enrolling in an excessive number of subjects. Student feedback also highlighted the importance of clear information regarding subject prerequisites. Many students expressed a desire for a section that visually represents their degree path, including required prior knowledge and enrollment dependencies.

One of the most surprising findings that emerged from the study is the relationship between students and advisors during the enrollment process. Students appeared to rely more heavily on information provided on the website than on direct advice from advisors. Students' self-regulation is considered a key factor for success in higher education. Nevertheless, the analysis of student behavior and information needs led to the decision to expand the scope of the prototype to include advisors as key stakeholders. We concluded that a learning dashboard could not only benefit students but also help advisors to provide more effective guidance and support during the enrollment process, in order to improve their interventions. These findings were published here:

N. Rivas, J. Minguillón, J. Chacón (2021) Enrolling Habits in Higher Education. What Sources of Information Do Students Have and What Are Missing?, INTED2021 Proceedings, pp. 4980-4988.

Regarding the second research question, RQ2: *How can information be appropriately showcased to assist students and advisors in their enrollment decision-making processes?* This research developed a learning dashboard seeking to enhance decision making for students and advisors. By following an iterative design approach and incorporating user-centered design principles, we developed a learning dashboard that addressed key student information needs. The research process involved the development of various design proposals, the creation of the engine for the subject recommendation system, the creation of a proof of concept that was used for simulations and student interviews. After these steps, a learning dashboard prototype was finally developed and evaluated through advisor interviews and usability testing. Feedback from these sessions informed further iterations and refinements of the design. The final learning dashboard incorporated the key features identified through the research process, providing students and advisors with a visually engaging and explainable prototype to support their enrollment decisions.

Accordingly, the prototype incorporates two complementary elements in a single visualization: a map representing the whole degree, which includes a recommendation system, and a deadline calendar, which is activated upon subject selection. As shown in Figure 5.23, the map represents the students' information needs, namely **student experience in previous semesters and validated subjects**. Students can distort the map and personalize the recommendations by assigning importance to the factors identified in the previous research, specifically **subject prerequisites, difficulty and popularity overlaps between subjects**. The system calculates distances between subjects and recommends those closest to the student's completed subjects, providing students with a learning path for extending the already "conquered" (i.e. passed subjects) region of the map. The rationale of the recommendation system was published here:

Minguillón, J., Rivas, N., & Chacón, J. (2021). Supporting Enrollment in Higher Education Through a Visual Recommendation System. Artificial Intelligence Research and Development: Proceedings of the 23rd International Conference of the Catalan Association for Artificial Intelligence, 339, 177. https://doi.org/10.3233/FAIA210131

When selecting subjects, the calendar visualization is activated, as seen in Figure 5.25. The calendar shows the deadline schedule overlaps between subjects and allows students to estimate **the needed workload for studying**. Therefore, we have addressed the research objective related to the second research question, that is, to develop an effective representation of enrollment-related data that allows both students and advisors to access relevant information related to the enrollment process. Consequently, we have established the second contribution of this research: An interactive learning dashboard integrated with a recommendation system, designed specifically for the enrollment process. Key features and considerations include:

- **Viewing the academic record at a glance:** The use of a map to represent the degree curriculum and the student academic record offers a clear and intuitive visualization.
- **Data integration:** The dashboard incorporates relevant data, including student academic records, subject information and enrollment prerequisites.
- **Subject placement:** Subjects are positioned on the map based on their relationships and relative distances, considering factors like difficulty, popularity, prerequisites, and overlaps between deadlines.
- **Recommendation system:** The integrated recommendation system suggests subjects that align with students' academic progress and preferences.
- **User interaction:** The dashboard allows users to customize the map by adjusting factors and viewing subjects in different categories.
- **Calendar integration:** A calendar view provides information about subject deadline dates and workload. This has been proven a highly valuable visualization for advisors.

By combining these elements, the learning dashboard allows students and advisors to make informed enrollment decisions by providing a comprehensive overview of the degree curriculum, subject recommendations, and relevant information in a visually engaging and interactive manner. The learning dashboard demonstrated its potential to effectively support advisor decision making by providing a comprehensive overview of the degree curriculum, subject recommendations and other essential information. The prototype was presented in the European Conference on Technology Enhanced Learning:

> Rivas, N., Minguillón, J., Chacón-Pérez, J. (2023). An enrollment dashboard to reinforce decision-making for students and advisors. In: Viberg, O., Jivet, I., Muñoz-Merino, P., Perifanou, M., Papathoma, T. (eds) Responsive and Sustainable Educational Futures. EC-TEL 2023. Lecture Notes in Computer Science, vol 14200. Springer, Cham. https://doi.org/10.1007/978-3-031-42682-7_71

While the system demonstrated promising results, it was important to perform a final validation. Therefore, we evaluated the prototype in order to address the third research question, RQ3: *To what extent is the use of a learning dashboard with a recommendation system relevant for the decisions taken by students and advisors when enrolling?* We performed a thorough validation of the prototype using a qualitative approach. The study involved twenty-seven students and nine advisors from the UOC Computer Science program and two UX experts. Data was collected through questionnaires, interviews and a heuristic evaluation. The analysis of this data aimed to assess the prototype's impact on student and advisor decision making, identify areas for improvement, and ultimately evaluate its potential to enhance the enrollment process.

Informed by the previous analysis, we were able to address the last research question of this thesis, that is, to analyze the impact of learning dashboards and recommendation systems in the enrollment process from the students and advisors perspective. The validation highlighted that the prototype had a positive impact on both stakeholders: students and their advisors. On the one hand, students thought that the dashboard provided a clear visual representation of their academic progress, highlighting validated, passed and pending subjects and potential enrollment subject combinations. The recommendation system offered personalized suggestions, guiding students towards suitable subject choices based on their individual needs and goals. This personalized approach allowed some students to make more informed decisions, as demonstrated by the students' feedback regarding the recommendation system. In fact, the information provided within the map visualization made some students change their mind when they saw the recommendation. On the other hand, from an advisor's perspective, the dashboard offered valuable insights into student progress and potential challenges. It enabled advisors to identify student needs and goals. Additionally, the dashboard facilitated a more efficient and effective advising process, as some advisors could quickly assess students' academic situations and could provide tailored recommendations, even without being contacted by students beforehand. The most remarkable finding is that the majority of stakeholders thought that the learning dashboard improved or facilitated the decision-making process. Overall, the integration of a learning dashboard with a recommendation system into the enrollment process had the potential to enhance student satisfaction, improve academic outcomes and enhance the advising process.

The heuristics evaluation revealed several strengths, including a clear and intuitive interface of the learning dashboard, effective organization of information, and a well-designed recommendation system, as explained in Chapter 06. However, some details for improvement were also identified, such as enhancing the clarity of subject recommendation, refining the overall design and UX, and simplifying instructional text. The results of this evaluation were also published in an international conference:

> Rivas, N., Minguillón, J. & Chacón-Pérez, J. (2025). Enhancing enrollment: an explainable visual recommendation system. In T. Bastiaens (Ed.), Proceedings of EdMedia + Innovate Learning (pp. 370-381). Barcelona, Spain: Association for the Advancement of Computing in Education (AACE).

Consequently, we have established the third contribution of this research, the evaluation of integrating learning dashboards and recommendation systems into the enrollment process. The study highlighted two important considerations:

- **Educational learning dashboards can enhance educational processes:** The validation of the prototype demonstrated that a user-friendly tool can positively impact decision making.
- **Educational learning dashboards can transform educational processes:** The validation of the prototype demonstrated that advisors could proactively offer tailored recommendations to students, even without being contacted by students beforehand.

7.2 Future research

This research identified two primary areas for future investigation. Firstly, the recommendation engine itself presents significant potential for further refinement. Secondly, the design and implementation of the learning dashboard offers numerous opportunities for further research, specifically, applying different data visualization methods.

Regarding the recommendation systems, refinements to the existing model could involve exploring alternative projection techniques, such as those based on non-linear dimensionality reduction methods, for instance t-distributed stochastic neighbor embedding (t-SNE). Moreover, the impact of temporal dynamics on the recommendation process warrants further investigation. For example, the current model might benefit from incorporating time-varying weights or adjusting the time window used for historical data analysis. The methodology for calculating distances between subjects could also be further explored, potentially incorporating alternative distance metrics or incorporating weights derived from simulations. Finally, while the current model relies primarily on distance-based measures, future research could investigate the effectiveness of new trends in recommendation algorithms, but in the context of subject recommendation for higher education. The developed prototype has the potential to incorporate other factors and algorithms, enabling an interesting research line for another doctoral thesis.

Furthermore, future research in explainable subject recommendation systems should prioritize user-centric investigations to understand the impact of explanations on diverse student populations. Given the variability in user preferences and needs, further investigation is needed to identify which explanation styles (e.g., content-based, collaborative filtering-based, post-hoc) and formats (e.g., textual, visual) are most effective in educational contexts. Precisely, research should explore how different types of explanations (e.g., those focusing on 'why' versus 'how' the system recommends a subject) influence student trust, understanding and decision making. The design and evaluation of hybrid explanation approaches, which integrate multiple explanation styles requires further investigation. Understanding how to effectively deliver these explanations, considering factors such as learning goals and individual student needs, is also crucial. Additionally, future work should address the challenge of balancing recommendation accuracy with explainability, where the 'black box' nature of some recommendation systems can compromise transparency. Finally, longitudinal studies examining the long-term impact of explainable subject recommendations on student learning outcomes and career trajectories would provide valuable insights into the practical implications of these systems.

Regarding the design and implementation of the learning dashboard, the current prototype utilizes a specific set of visualization techniques (a map and a calendar), but future research should investigate the effectiveness of alternative visualization techniques. For example, network graphs, treemaps, and interactive 3D visualizations could provide more engaging and informative representations of complex academic information. Additionally, exploring the integration of gamification elements, such as points, badges and leaderboards, could potentially enhance user engagement.

The insights gained from developing and evaluating this prototype extend to a more fundamental discussion about the organization of university degrees in open and online universities. The traditional semester-based organization often misaligns with the enrollment patterns of real students. The learning dashboard presented in this study challenges this conventional approach, offering a more flexible and personalized view of the academic journey. This aligns with previous research suggesting the need for innovative approaches to distance education and curriculum design. Besides, by using data visualization techniques, it is possible to identify areas for improvement within the curriculum itself. Despite increasing emphasis on competency-based education, current enrollment practices often rely on traditional subject-based approaches. This creates a significant disconnect between the desired learning outcomes (competencies) and the actual learning pathways chosen by students, leading to a potential mismatch between student skills and the demands of the modern workforce. A significant area for future research could be the development of recommendation systems that prioritize the acquisition of specific competencies, focusing on a more pedagogical approach. This could involve the creation and implementation of competency-based matrices that map subjects to specific skills. Such an approach has the potential to shift the focus of academic planning from traditional subject-based enrollments towards a more holistic and competency-driven approach to learning.

7.3 Institutional implementation

The overall evaluation of the prototype could be considered a success and demonstrated its effectiveness, but also identified some areas for improvement. The learning dashboard has potential for further development and refinement. It serves as a Minimum Viable Product (MVP), providing a foundation for future iterations and refinements within a future development process. Table 7.1 summarizes the recommended actions to be considered before its institutional implementation. For instance, the map visualization used for subject selection could benefit from several improvements. In particular, subject identification could be clearer by specifying the acronym, full name and code of the subject in a more interactive way. As well as an explicit representation of prerequisites. Furthermore, some users thought there was meaning behind the subject area, and they missed entirely the distance between subjects concept. Therefore, it would be important to add some visual aid to clarify the concept of distance.

Implementing a system of on-demand information layers, inspired by the details on demand Sneiderman's mantra, would allow users to access additional information as needed. Additionally, explicit rules for managing subject prerequisites and dependencies could be integrated. Furthermore, an interesting feature would be to ask students to select their preferred itinerary at the beginning of the process. This would allow for further refinement in the recommendation system and for advisors to know the student's preferences when receiving the student's enrollment choices. Finally, the recommendation system could be expanded to provide long-term recommendations, extending beyond the immediate semester. This could create a full calendar and make students even clearer about their progression within the entire degree, as well as the options for selecting subjects in the future.

Table 7.1 - Potential prototype improvements
Possible improvements derived from the prototype evaluation. The results of questionnaires, interviews and the heuristic evaluation have been considered.

Feature	Current state	Suggested improvement
Overall design		
Titles and subtitles	Somewhat visible	More prominent title and subtitle consistency
Action indicators	Sufficiently clear	Clearer visual cues in the recommendation system section Breadcrumbs and icons can be added in the whole process Ask users to identity their itinerary beforehand
Responsiveness	Not always in the right place	Improve rolling over positioning
User Experience		
Menu structure	Logical but not always clear	Improve clarity and consistency between menu and task flow
Left panel visibility	Always visible	Display only when necessary (e.g., in the recommendation system tab)
Map visualization and slider explanations (i)	Somewhat clear	Clearer subject identification Clearer prerequisites and dependencies representation between subjects The meaning of distance between subjects must be represented clearer Explanations could be more explicit and added to the map
Help and documentation		
Initial guidance	Implicit	Provide clear initial instructions
Contextual help	Limited	Consider adding tooltips or pop-up explanations for ambiguous options

The evaluation results of this prototype provided in Chapter 6 suggest its potential for implementation in real educational scenarios. The positive feedback from students and advisors, coupled with the demonstrated effectiveness of the recommendation system and visualizations, indicates that the prototype could be adapted and implemented in real-world settings to support the enrollment process. There are several opportunities to expand the prototype's impact and scalability. Firstly, integrating the learning dashboard with institutional login systems would enable broader access and usage. The prototype is prepared to be used by all students in the Computer Science program and it could even be applied to other degrees. Conducting large-scale trials with students across multiple degrees could provide valuable insights for further refinement. By tracking student progress over multiple semesters, the system can be fine-tuned to ultimately provide long-term support and guidance. Secondly, if adopted at an institutional level, future studies could focus on student outcomes. To further assess the impact of the learning dashboard, future research could investigate its influence on student academic performance and retention rates. By tracking student progress and outcomes over time when using the learning dashboard, it would be possible to determine whether the learning dashboard has a positive impact on reducing dropout rates and improving academic achievement. Conducting a longitudinal study to assess the long-term impact of the learning dashboard would require significant time and resources. Given that UOC students typically take multiple semesters to complete their degrees, tracking their progress and evaluating the learning dashboard's effectiveness over an extended period would be necessary. Finally, the core functionalities and findings of this research have the potential to be applied to a broader range of educational contexts. Online universities with flexible enrollment systems, as well as traditional universities with elective subject selection, could benefit from the insights gained and the functionalities developed in this study.

Furthermore, this tool has the potential to become a valuable asset for the UOC's overall marketing strategy, particularly in enhancing on-page SEO. If integrated into the Computer Science degree page, the user-friendly UX of this interactive tool could significantly enhance engagement for prospective students, potentially leading to improved visibility and performance in relevant online searches. While the thesis has primarily focused on the prototype's application for students in their second semester onwards, I am convinced that with minor adjustments and the integration of the ESPRIA package within the visualization, this tool could be strategically positioned on the homepage of the Computer Science degree program, instead of the current subject list. From the perspective of a prospective student, particularly those with limited time due to work commitments, this interactive tool could significantly enhance the information-gathering process. By providing a dynamic and engaging overview of the program, it could improve both user interaction rates, keyword positions, number of clicks and visits and ultimately, conversion rates. Furthermore, this approach would effectively showcase the UOC's commitment to technological advancement and student-centred learning, differentiating the Computer Science program from offerings at other open and online universities, particularly within the STEM fields.

7.4 Final thoughts and personal insights

Moving forward, I am convinced that the principles and findings of this thesis offer a valuable foundation for future developments in educational technology. The integration of explainable recommendation systems and data visualization will help user trust and understanding. Educational technology, at its core, must be user-centered. Effective tools can not be created without deeply understanding the users who will interact with them – in this case, students and their advisors. My own experiences with university enrollment in 2003, dealing with static manuals, extensive lists of subjects, credit details, descriptions and schedules, served as a potent inspiration for this research. It was surprising to find a relative scarcity of projects focused on online enrollment tools, despite its critical importance for students. In the midst of the current excitement surrounding AI, I would also like to emphasize the irreplaceable role of human guidance in education. While technology can provide support, as this learning dashboard aims to do, I firmly believe that tools cannot yet fully replace the understanding and empathy that human advisors offer. Their role as mentors and sources of personalized support remains essential in educational learning scenarios.

I would also like to address the fact that this research has also reinforced the understanding that digital platforms, much like learning environments themselves, are never truly finished. The iterative design process employed here, with continuous feedback and refinement, underscores the dynamic nature of effective project developments. Just as websites require constant updates, educational support systems need also to evolve to face changing user needs and technological advancements.

Ultimately, this PhD journey has been more than just an academic exercise; it has been an exploration of how technology can enhance decision making in educational contexts. It has reinforced my belief that by listening to student and advisor needs, utilizing multidisciplinary approaches, and continuously iterating on design approaches, we can build more supportive, engaging, and effective learning environments for the next generation of students. Beyond the academic contributions, writing this thesis has been a transformative learning experience. It has provided me with a robust framework for applying both quantitative and qualitative data in the creation of meaningful learning environments. As an educational content creator, I intend to use this multidisciplinary knowledge, translating research insights into practical solutions that genuinely enhance educational experiences.

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Annex

A.1 Enrolling habits questionnaire

A two-iteration questionnaire, administered in Spanish and Catalan, was used to investigate student enrollment habits and preferences at the UOC (see tables A.1 to A.4). The first iteration focused on gathering data related to students' motivations for pursuing their degree, their current academic situation, factors influencing subject selection, and overall satisfaction with the enrollment process. The second iteration was created after analyzing the first one, focusing more specifically on students' preferences regarding factors influencing subject enrollment. Both iterations employed a combination of multiple-choice, Likert scale, and open-ended questions.

A.1.1 First iteration questionnaire

Table A.1 - First iteration questionnaire (motivation)
Motivation to learn question.

Q1	¿Cuáles son tus motivaciones para haber escogido el grado en ingeniería informática? Selecciona un máximo de 2 respuestas que reflejen mejor tu situación actual.
	1. Busco reorientar mi carrera profesional. 2. Me piden el título para trabajar o para ser promocionado. 3. Necesito mejorar mis conocimientos relacionados con este grado. 4. Estudio por hobby, quiero cursar el grado simplemente porque me interesa. 5. Quiero acabar el grado de Ingeniería Informática que empecé con anterioridad. 6. Mantenerme informado de las últimas tecnologías en el ámbito.

Table A.2 - First iteration questionnaire (current situation)
Students' current situation questions.

<table>
<tr><td>Q2</td><td colspan="7">¿De cuántos semestres ya te has matriculado en la UOC?</td></tr>
<tr><td></td><td colspan="7">Empiezo el grado, es mi primera matrícula.
Empecé el semestre anterior, es mi segunda matrícula.
Ya me he matriculado tres o más veces, incluyendo otros grados.</td></tr>
<tr><td>Q3</td><td colspan="7">¿De cuántas asignaturas te has matriculado este semestre (o el anterior, si este semestre no estás matriculado de ninguna asignatura)?</td></tr>
<tr><td></td><td colspan="7">1. De 1
2. De 2
3. De 3
4. De 4
5. De 5
6. De 6 o más</td></tr>
<tr><td>Q4</td><td colspan="7">¿Qué frase define mejor tu situación con respecto a la convalidación de tus estudios previos?</td></tr>
<tr><td></td><td colspan="7">1. Aún no me he informado sobre la convalidación de asignaturas.
2. No tengo ninguna asignatura a convalidar.
3. No quiero convalidar ninguna asignatura.
4. Tengo pendiente solicitar la convalidación de una o más asignaturas.
5. He solicitado la convalidación de una o más asignaturas.
6. Me han denegado la convalidación de la mayoría de asignaturas que he solicitado.
7. Me han aceptado la convalidación de la mayoría de asignaturas que he solicitado.</td></tr>
<tr><td>Q5</td><td colspan="7">Valora la importancia de cada fuente de información para determinar la última matrícula que has hecho</td></tr>
<tr><td rowspan="2"></td><td>Factor</td><td>1</td><td>2</td><td>3</td><td>4</td><td>5</td><td>NS/NC</td></tr>
<tr><td colspan="7">1. El plan de estudios disponible en la web de la UOC
2. Las recomendaciones de mi tutor
3. Las recomendaciones de terceros (compañeros de trabajo, otros estudiantes, familia o amigos)
4. Mis conocimientos previos sobre el grado y las asignaturas</td></tr>
</table>

Table A.3 - First iteration questionnaire (subject)
Subject-related questions.

Q6	Valora cada factor con respecto a su importancia para determinar el número de asignaturas total en las que te has matriculado (1 nada importante, 5 muy importante, NS/NC)						
	Factor	1	2	3	4	5	NS/NC
	1. El tiempo que tengo disponible para estudiar 2. El coste total de la matrícula 3. Las recomendaciones de mi tutor 4. La experiencia del semestre anterior 5. El grado de dificultad de las asignaturas 6. Avanzar más rápidamente para obtener el título 7. Obtener conocimientos necesarios para mi desarrollo profesional						
Q7	Valora cada factor con respecto a su importancia a la hora de escoger las asignaturas de las cuales te has matriculado (1 nada importante, 5 muy importante, NS/NC)						
	Factor	1	2	3	4	5	NS/NC
	1. Las recomendaciones de mi tutor 2. Mis intereses personales 3. Mis intereses profesionales 4. La organización semestral del plan de estudios 5. Las asignaturas matriculadas con anterioridad 6. El conocimiento que tengo de los temarios 7. Las competencias que se trabajan en cada asignatura 8. Por su tipología (obligatorias, optativas, libre elección...) 9. Por su metodología (uso de debates, trabajo en grupo...) 10. Por su modelo de evaluación (entrega de trabajos, con o sin examen...) 11. Por las convalidaciones que he solicitado o pienso solicitar 12. Por tratar sobre un tema de actualidad en el ámbito						
Q8	Valora qué otros factores podrían ser de ayuda para la selección de una asignatura en particular (1 nada importante, 5 muy importante, NS/NC)						
	Factor	1	2	3	4	5	NS/NC
	1. El número de estudiantes matriculados 2. El porcentaje de estudiantes que supera la evaluación continua 3. El porcentaje de estudiantes que supera la asignatura 4. El porcentaje de estudiantes repetidores 5. El índice de satisfacción de la asignatura 6. El número de actividades evaluables de evaluación continua 7. La disponibilidad del calendario de actividades y entregas 8. La composición del equipo docente						

Table A.4 - First iteration questionnaire (satisfaction)
Satisfaction with the enrolment process.

Q9	¿Con qué nota puntuarías el proceso de matrícula de este semestre? (0 muy deficiente, 10 excelente, NS/NC)												
	Escala	0	1	2	3	4	5	6	7	8	9	10	NS/NC
Q10	¿Echas en falta algún tipo de información con respecto al proceso de matrícula?												
	Añade en esta sección cualquier otra información que consideres que podría ser relevante durante el proceso de matrícula.												

A.1.2 Second iteration

Table A.5 - Second iteration questionnaire (motivation)
Motivation to learn question.

Q1	¿Qué frase define mejor tu situación con respecto a la convalidación de tus estudios previos?
	1. Aún no me he informado sobre la convalidación de asignaturas. 2. No tengo ninguna asignatura a convalidar. 3. No quiero convalidar ninguna asignatura. 4. Tengo pendiente solicitar la convalidación de una o más asignaturas. 5. He solicitado y estoy pendiente de la convalidación de una o más asignaturas. 6. Me han denegado la convalidación de la mayoría de asignaturas que he solicitado. 7. Me han aceptado la convalidación de la mayoría de asignaturas que he solicitado.

Table A.6 - Second iteration questionnaire (preferences)
Students' preferences questions.

Q2	Valora cada factor con respecto a su importancia a la hora de escoger el nº de asignaturas total de las cuales te has matriculado (1 nada importante, 5 muy importante, NS/NC).						
	Factor	1	2	3	4	5	NS/NC
	1. Las asignaturas matriculadas con anterioridad. 2. Las asignaturas que he suspendido y debo repetir. 3. Las convalidaciones que he solicitado o pienso solicitar. 4. El número de semestres que llevo cursados. 5. El itinerario indicado en el plan de estudios de la web. 6. La información facilitada por mi tutor. 7. El tiempo que tengo disponible para estudiar. 8. El coste total de la matrícula. 9. Mi experiencia en semestres anteriores.						
Q3	Valora la información mostrada en el plan de estudios disponible en la web de la UOC (1 nada de acuerdo, 5 muy de acuerdo, NS/NC no sabe no contesta).						
	Factor	1	2	3	4	5	NS/NC
	1. La información de la web sobre las asignaturas del grado está bien organizada. 2. Me resulta fácil saber de qué asignaturas debo matricularme a partir de la información mostrada en la web. 3. La información de las asignaturas de la web es clara y completa. 4. La información mostrada en la web de la UOC ha sido suficiente para matricularme.						
Q4	Valora la atención recibida por el tutor a la hora de matricularte (1 nada de acuerdo, 5 muy de acuerdo, NS/NC no sabe no contesta).						
	Factor						
	1. El tutor me ha ayudado a ajustar el número de asignaturas a matricular. 2. El tutor me ha indicado de qué asignaturas debo matricularme. 3. El tutor ha resultado indispensable a la hora de realizar mi matrícula. 4. He cambiado de opinión con respecto a mi propuesta de matrícula después de hablar con mi tutor. 5. La información aportada por el tutor ha sido suficiente para matricularme. 6. El procedimiento y aplicaciones usados para comunicarme con mi tutor son adecuados.						
Q5	Valora la importancia que ha tenido el tiempo que tienes disponible para estudiar a la hora de matricularte (1 nada de acuerdo, 5 muy de acuerdo, NS/NC no sabe no contesta).						
	Factor						
	1. La cantidad de horas que puedo dedicarle al estudio ha sido un factor importante a la hora de seleccionar las asignaturas matriculadas. 2. He obtenido suficiente información sobre el calendario de actividades y entregas a la hora de matricularme. 3. La información proporcionada deja claro cuánto tiempo debería dedicar al estudio antes de formalizar mi matrícula. 4. El tiempo que tengo disponible para estudiar ha sido el factor más importante a la hora de decidir mi matrícula.						

<table>
<tr><td>Q6</td><td colspan="7">Valora la importancia que ha tenido el coste económico a la hora de matricularte (1 nada de acuerdo, 5 muy de acuerdo, NS/NC no sabe no contesta).</td></tr>
<tr><td rowspan="2"></td><td>Factor</td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td colspan="7">1. El coste total de la matrícula ha sido importante a la hora de decidir el número total de asignaturas matriculadas.
2. Durante el proceso de matrícula he comprendido fácilmente cuánto iba a costar el semestre.
3. El importe de las tasas ha influenciado el número de asignaturas de las que me he matriculado.
4. El recargo asociado a la repetición de asignaturas ha determinado el número de asignaturas de las que me he matriculado.</td></tr>
<tr><td>Q7</td><td colspan="7">Valora la importancia que ha tenido el tipo de asignatura a la hora de matricularte
(1 nada de acuerdo, 5 muy de acuerdo, NS/NC no sabe no contesta).</td></tr>
<tr><td rowspan="2"></td><td>Factor</td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td colspan="7">1. He entendido la carga de trabajo que supondría superar cada asignatura antes de matricularme.
2. He seleccionado las asignaturas por su modelo de evaluación.
3. La información relacionada con las competencias de cada asignatura ha sido importante a la hora de matricularme.
4. La tipología de cada asignatura (obligatorias, optativas, libre elección…) ha sido importante a la hora de matricularme.
5. La metodología de cada asignatura (uso de debates, trabajo en grupo…) ha sido importante a la hora de matricularme.
6. He tenido en cuenta las asignaturas previas necesarias o recomendadas a la hora de matricularme.</td></tr>
<tr><td>Q8</td><td colspan="7">Valora la importancia que tendría esta información a la hora de matricularte (1 nada importante, 5 muy importante, NS/NC no sabe no contesta).</td></tr>
<tr><td rowspan="2"></td><td>Factor</td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td colspan="7">1. El número de estudiantes que hay en el aula.
2. El porcentaje de estudiantes que supera la evaluación continua.
3. El porcentaje de estudiantes que supera la asignatura.
4. El porcentaje de estudiantes repetidores.
5. El índice de satisfacción de la asignatura.
6. El semestre en el cual se suele matricular la asignatura.
7. Las asignaturas previas más relevantes.</td></tr>
<tr><td>Q9</td><td colspan="7">Valora la importancia que han tenido distintas fuentes de información ajenas a la UOC a la hora de matricularte (1 nada importante, 5 muy importante, NS/NC no sabe no contesta).</td></tr>
<tr><td rowspan="2"></td><td>Factor</td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>1. Páginas web externas a la UOC.
2. Redes sociales.
3. Reseñas u opiniones de otros estudiantes.
4. Mi entorno laboral o profesional.</td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
</table>

Table A.7 - Second iteration questionnaire (satisfaction)
Satisfaction with the enrolment process questions.

Q10	¿Con qué nota puntuarías el proceso de matrícula de este semestre? (0 muy deficiente, 10 excelente, NS/NC no sabe o no contesta).												
	Escala	0	1	2	3	4	5	6	7	8	9	10	NS/NC
Q11	¿Echas en falta algún tipo de información con respecto al proceso de matrícula?												
	Añade en esta sección cualquier otra información que consideres que podría ser relevante durante el proceso de matrícula.												

A.2 Design proposals

Alternative design proposals were explored during the development of the learning dashboard. As discussed in Chapter 5, the final design implemented in this study centered on a map metaphor. However, the design process involved an iterative exploration of various concepts, each contributing to our understanding of the complexities of the enrollment process and the requirements for an effective visualization tool. These alternative proposals, while not ultimately adopted, offer valuable insights into the design considerations and challenges encountered. Initial designs were created using Photoshop and Illustrator in order to visualize some ideas, and proof of concept tests were programmed in R Shiny.

A.2.1 Initial designs

A visualization inspired by the OECD Better Life Index (*OECD Better Life Index*, s. f.) aimed to allow students to weigh different criteria (e.g., time commitment, difficulty) to personalize subject recommendations. Other initial designs proposed calendars, bar charts, journey-based representations of the degree and a star map.

Figure A.1 - Example of design proposal (Better Life Index)

Design proposal inspired by the OECD Better Life Index (*OECD Better Life Index*, s. f.).

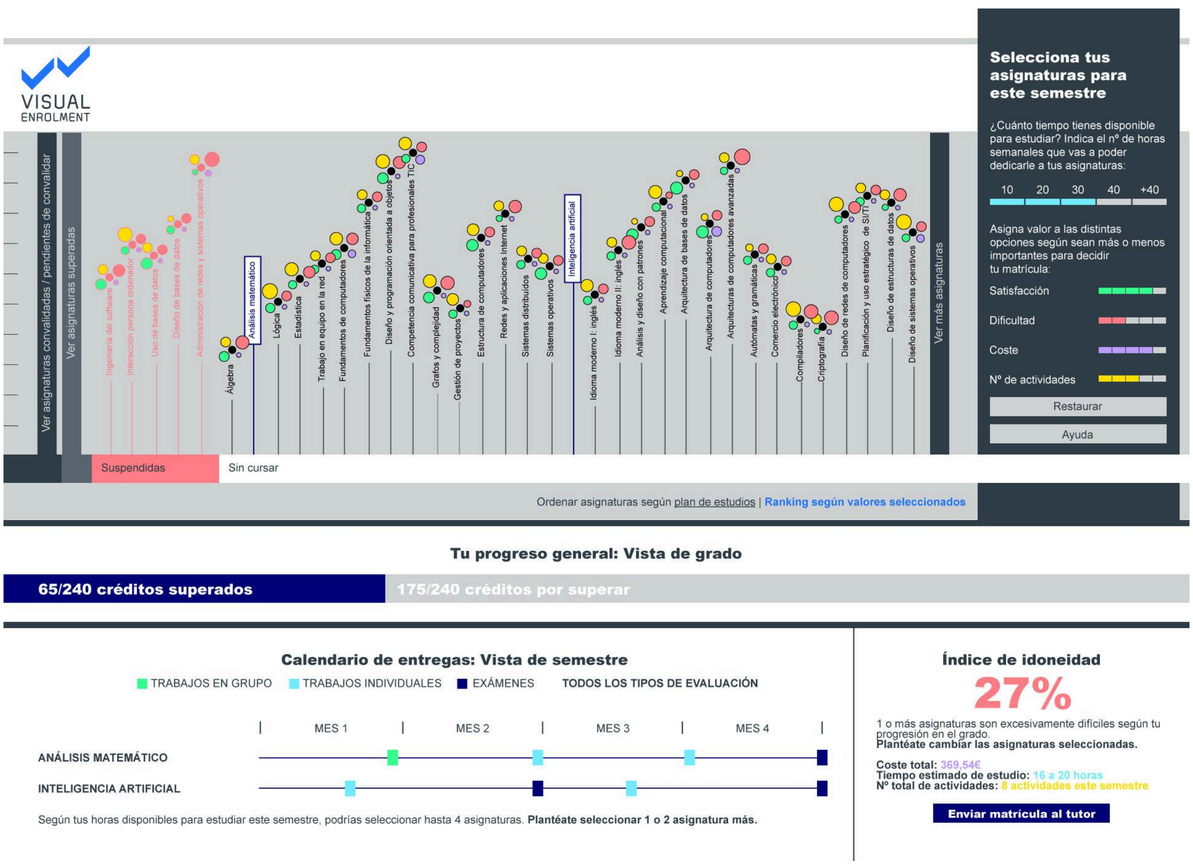
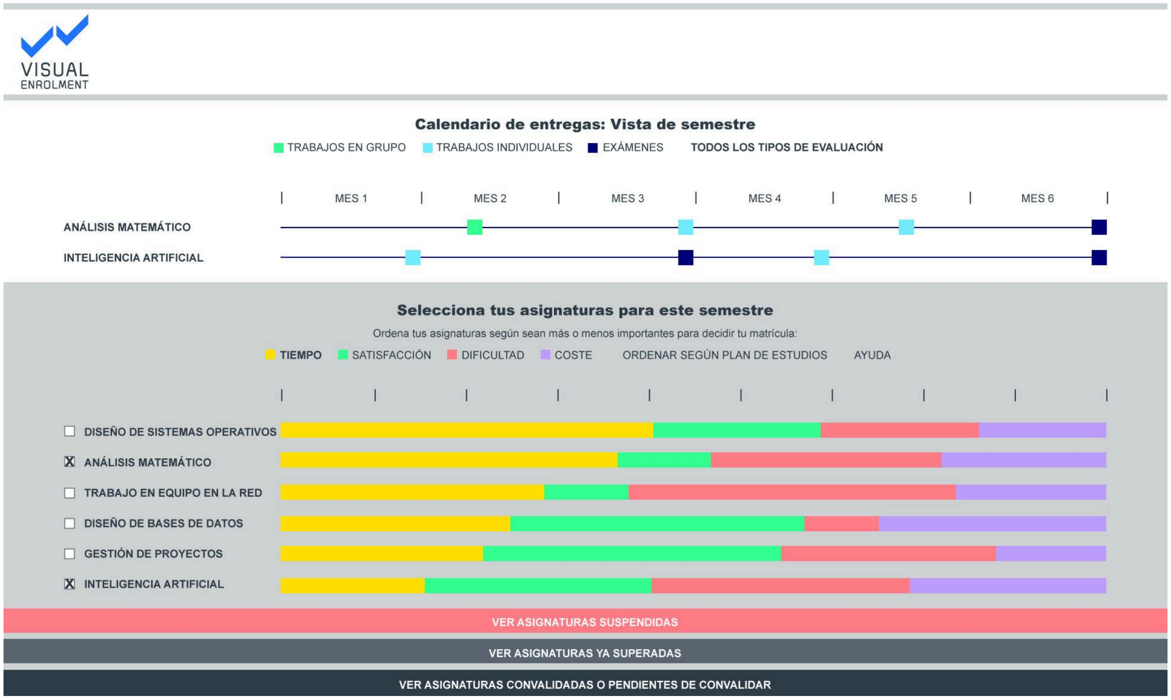


Figure A.2 - Example of design proposal (calendar oriented)
Design proposals using calendars and bar charts.



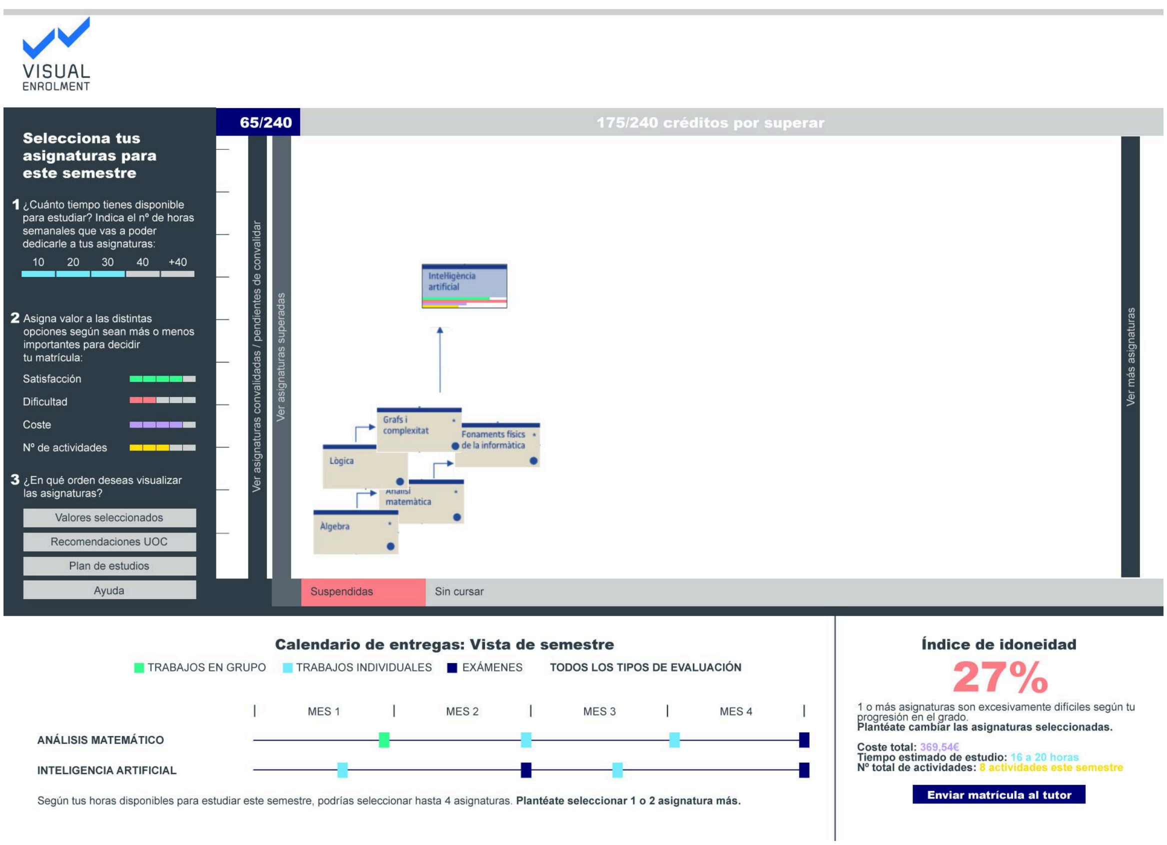


Figure A.3 - Example of design proposal (journey based)
Design proposals using journey-based representations.

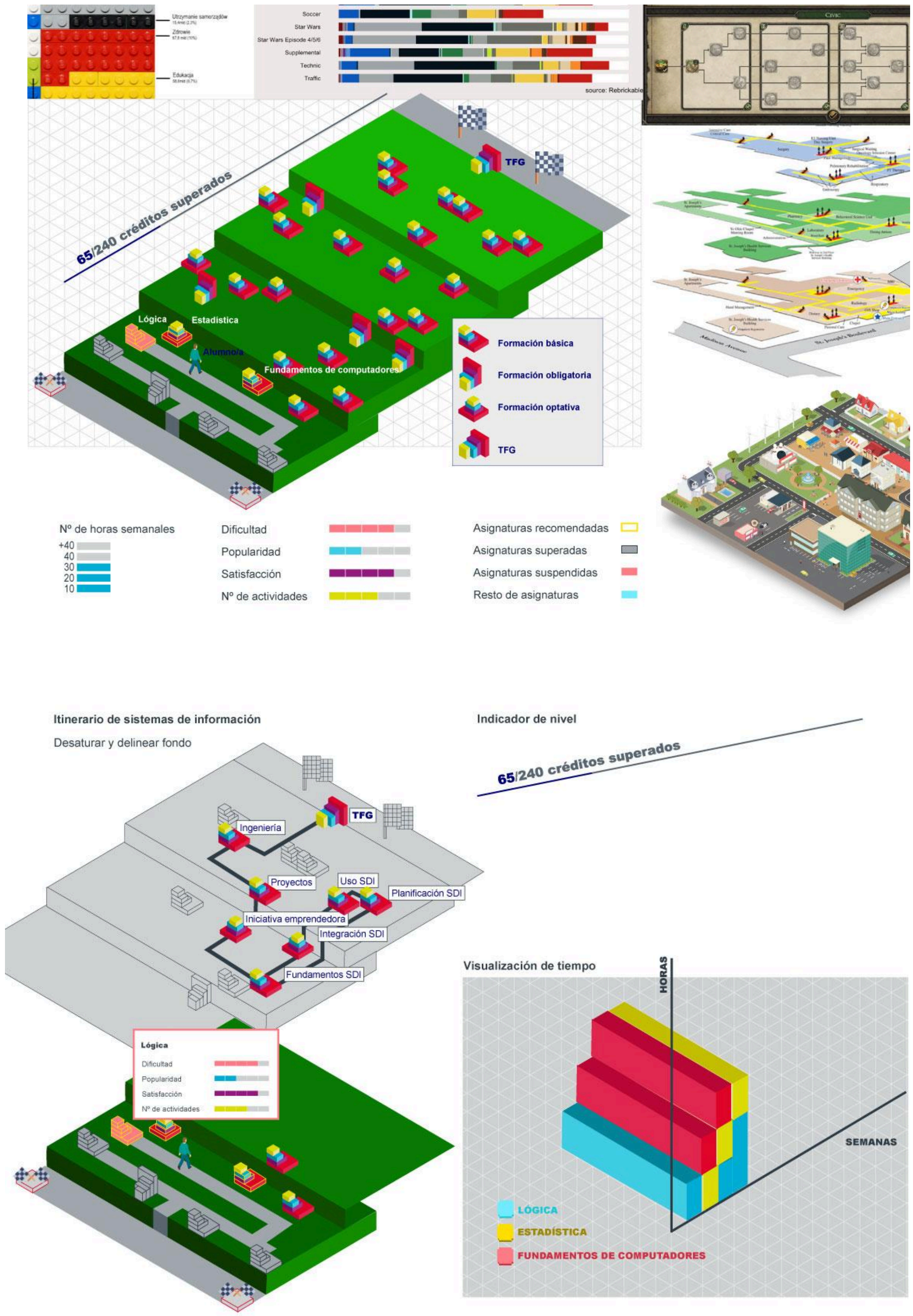
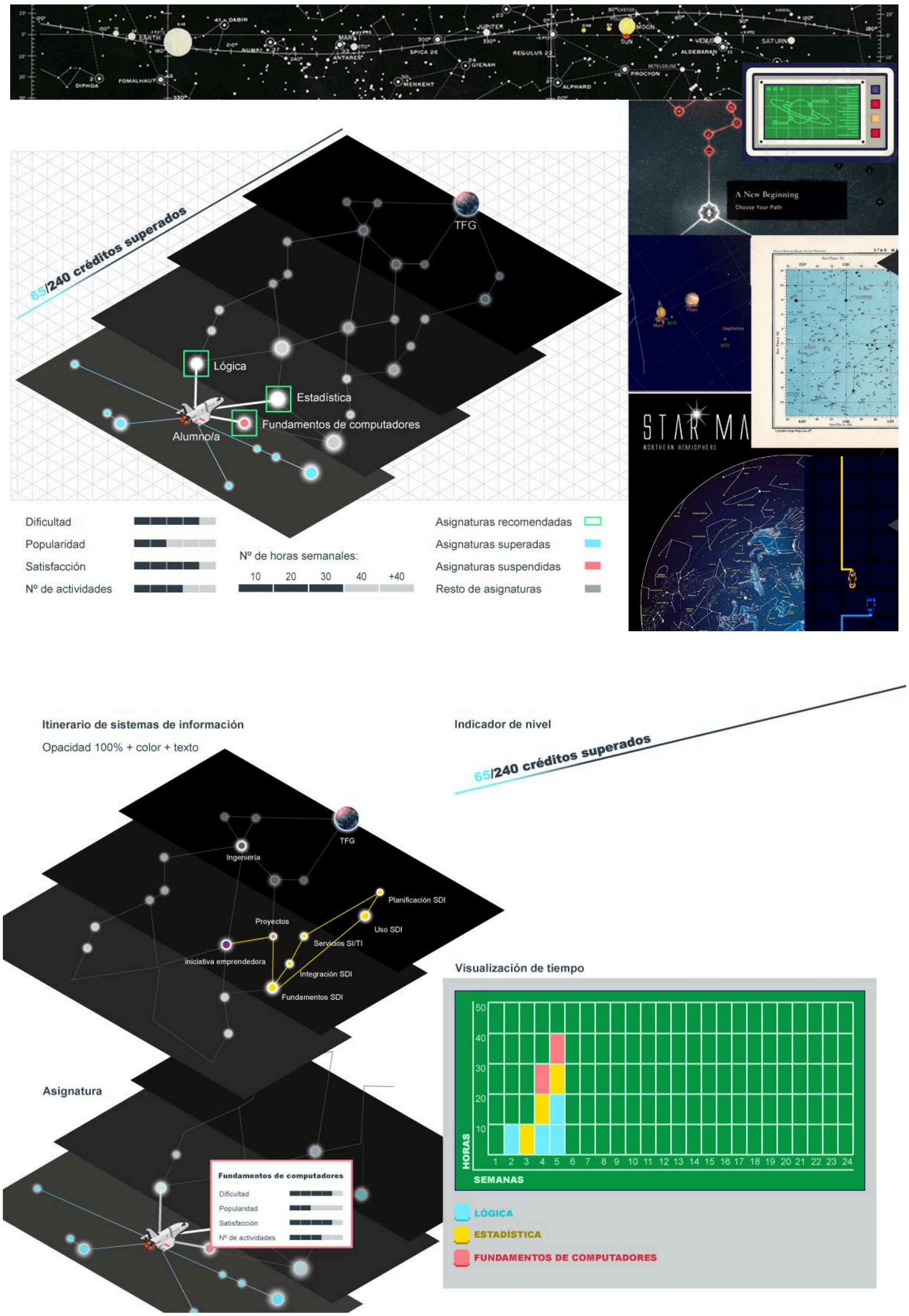


Figure A.4 - Example of design proposal (journey based)

Design proposal using a star map.

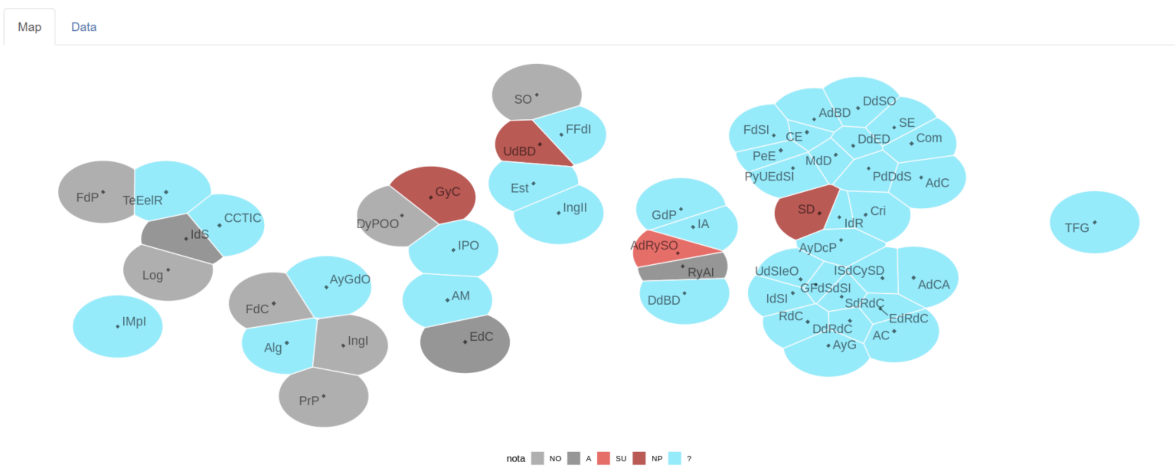


A.2.2 Proof of concept tests

The proof of concept for the learning dashboard utilized a map metaphor to visualize the degree structure and recommend subjects. The system generates an initial map based on historical enrollment data, student records, curriculum, and prerequisites. Subjects are positioned based on factors like prerequisites, popularity, difficulty, and scheduling overlap. The map is personalized by students adjusting criteria weights, and recommendations are made based on proximity to previously passed subjects. Several design tests were created in order to better visualize the student academic record, test color schemes, icons, different features and visualizations.

Figure A.5 - Example of design proposal (bubble based)

A bubble-based visualization experiment. This design was discarded as it did not successfully translate the intended map metaphor.



A.3 Students' informal interviews

Student interviews were conducted with four volunteers who had expressed interest in the project. These interviews aimed to gather user feedback on the map and calendar proof-of-concept visualizations. During individual video calls, students interacted with both interfaces by manually loading data.

A.3.1 Protocol

The user feedback sessions were conducted in Spanish, using the following protocol:

Voy a mostrarte una visualización en la que estamos trabajando: http://personal.uoc.edu:8080/VE/

1. *Describe con tus palabras lo que estás viendo. Explica cada apartado que ves y qué crees que puede significar o para qué se tiene que usar.*
2. *El grado en Grado de Ingeniería Informática se divide en 5 itinerarios. Mediante la caja de selección del panel de la izquierda puedes seleccionar destacar el itinerario que te interesaría. Selecciona el itinerario de Hardware ¿Cuántas asignaturas lo componen?*
3. *Coloreemos ahora las asignaturas según su dificultad ¿Puedes identificar la asignatura del grado de Hardware más difícil?*
4. *Este botón "fuerza" a las asignaturas a ordenarse según el plan de estudios de la UOC. Mueve todos los sliders a 0 menos el de dificultad ¿Puedes identificar la asignatura más difícil?*
5. *Ahora mueve todos los sliders a 0 menos el de "popularidad" ¿Puedes identificar asignaturas que otros alumnos suelen realizar a la vez?*
6. *Ahora vamos a cargar el expediente de un estudiante. ¿Qué asignaturas ha aprobado? ¿Qué asignaturas ha suspendido?*
7. *Selecciona los distintos tipos de asignatura (básicas, obligatorias, itinerario)... ¿Puedes identificar el tipo de asignatura que le queda por cursar a este estudiante?*
8. *En esta representación aparecen las asignaturas aprobadas en color gris. Propón 2 o 3 asignaturas para matricularse el siguiente semestre. Explica tus motivos para elegir esas asignaturas. ¿Qué te ha llevado a seleccionarlas?*
9. *Ahora que ya dominas este tipo de visualización. ¿Podrías explicar al menos 3 aspectos que crees que son de tu agrado y 3 aspectos que mejorarías?*
10. *¿Cómo seleccionarías y marcarías las convalidaciones? ¿Te sería útil visualizar esta información?*

Veamos la segunda visualización: http://personal.uoc.edu:8080/CAL/

11. *Selecciona 2 asignaturas. Al hacerlo, aparecerán las actividades evaluables de las mismas en la visualización. ¿Qué número de actividades genera cada una de las asignaturas seleccionadas?*
12. *Si el sistema te propusiera que matriculases estas dos asignaturas juntas ¿Te parece correcto? Argumenta tu respuesta.*
13. *¿Se corresponde el calendario de las asignaturas seleccionadas con el tiempo que tienes disponible para estudiar en el siguiente semestre?*

A.4 Advisors' interviews and questionnaire

Advisor interviews were conducted with a beta advisor and subsequently eight volunteer advisors to evaluate the learning dashboard prototype from their perspective. The interviews aimed to understand the dashboard's usability, design perceptions, impact on the recommendation process, and how it compared to their current tools. The evaluation involved sending advisors student records, a questionnaire, and an explanatory video, followed by individual interviews.

A.4.1 Students' record example

This is an example of the Students' record example sent to advisors before the interviews:

Estudiante 1

Este estudiante se va a matricular en el semestre de septiembre. Este es su expediente académico:

Semestre	*Nota*	*Tipo de asignatura*	*Nombre de la asignatura*
1	*NO*	*Básica*	*Administración y gestión de las organizaciones*
	A	*Optativa*	*Iniciación a las matemáticas para la ingeniería*
2	*NO*	*Obligatoria*	*Competencia comunicativa para profesionales de las TIC*
	A	*Básica*	*Estadística*
	SU	*Básica*	*Lógica*

No tiene asignaturas convalidadas

Estudiante 2

Este estudiante se va a matricular en el semestre de septiembre. Este es su expediente académico:

Semestre	*Nota*	*Tipo de asignatura*	*Nombre de la asignatura*
1	*EX*	*Básica*	*Fundamentos de programación*
	NO	*Obligatoria*	*Ingeniería del Software*
	EX	*Básica*	*Lógica*
	EX	*Optativa*	*Iniciación a las matemáticas para la ingeniería*
2	*NO*	*Básica*	*Prácticas de programación*
	NO	*Básica*	*Álgebra*
	NO	*Básica*	*Trabajo en equipo en la red*
	EX	*Básica*	*Fundamentos de computadores*
	EX	*Obligatoria*	*Interacción persona ordenador*

Estas son sus asignaturas convalidadas:

Tipo de asignatura	*Nombre de la asignatura*
Optativa	*Iniciativa emprenedora*

Estudiante 3

Este estudiante se va a matricular en el semestre de septiembre. Este es su expediente académico:

Semestre	***Nota***	***Tipo de asignatura***	***Nombre de la asignatura***
1	*NP*	*Básica*	*Fundamentos físicos de la informática*
	A	*Optativa*	*Iniciación a las matemáticas para la ingeniería*
2	*NO*	*Básica*	*Fundamentos de programación*
3	*NO*	*Obligatoria*	*Diseño y programación orientada a objetos*
4	*SU*	*Básica*	*Fundamentos de computadores*
	NO	*Obligatoria*	*Ingeniería del Software*
	SU	*Básica*	*Lógica*

Estas son sus asignaturas convalidadas:

Tipo de asignatura	***Nombre de la asignatura***
Básica	*Trabajo en equipo en la red*

Estudiante 4

Este estudiante se va a matricular en el semestre de septiembre. Este es su expediente académico:

Semestre	***Nota***	***Tipo de asignatura***	***Nombre de la asignatura***
1	*NO*	*Básica*	*Lógica*
	EX	*Optativa*	*Iniciación a las matemáticas para la ingeniería*
2	*NO*	*Básica*	*Álgebra*
	NO	*Obligatoria*	*Inglés I*
3	*NO*	*Básica*	*Análisis matemático*
	NO	*Obligatoria*	*Inglés II*
	EX	*Básica*	*Estadística*
4	*NO*	*Básica*	*Fundamentos de programación*
	A	*Obligatoria*	*Grafos y complejidad*

Estas son sus asignaturas convalidadas:

Tipo de asignatura	***Nombre de la asignatura***
Básica	*Trabajo en equipo en la red*
Optativa	*Iniciativa emprenedora*
Básica	*Fundamentos físicos de la informática*

A.4.2 Advisors’ questionnaire

A questionnaire, administered in Spanish, was sent along with the Students’ record example:

En nuestro anterior correo, hemos adjuntado 4 expedientes de estudiantes del grado de ingeniería informática (son estudiantes escogidos al azar, pueden no ser tuyos). Puedes leerlos tranquilamente y responder a las siguientes preguntas:

Q1	*¿Qué asignaturas le recomendarías matricular al estudiante 1 y por qué?*
Q2	*¿Qué asignaturas le recomendarías matricular al estudiante 2 y por qué?*
Q3	*¿Qué asignaturas le recomendarías matricular al estudiante 3 y por qué?*
Q4	*¿Qué asignaturas le recomendarías matricular al estudiante 4 y por qué?*

Preguntas complementarias

Q5	*¿Cómo te organizas y qué información tienes en cuenta para recomendar asignaturas a tus estudiantes?*
Q6	*¿Cuánto tardas en general en tomar una decisión para hacer una recomendación de matrícula a un estudiante?*
Q7	*¿Tienes algún otro comentario al respecto del proceso de matrícula?*

A.4.3 Advisors' interview protocol

The user feedback sessions were conducted in Spanish, using the following protocol:

¡Hola! Soy Noelia Rivas, doctoranda en Tecnologías de la Información y Redes de la UOC. Muchísimas gracias por participar en esta entrevista.

Para ponerte un poco en contexto, comentarte que nos encontramos estudiando el proceso de matrícula de la UOC. Si necesitas más información sobre este proyecto puedes visitar: https://visualenrolment.com/es/

Necesitamos grabar esta entrevista para recopilar datos y transcribirla posteriormente. No te preocupes, ninguno de tus datos será publicado, aunque es posible que si se publiquen algunas de tus opiniones y apreciaciones manteniendo el anonimato. Los datos se conservarán hasta la presentación de la tesis. ¿Estás conforme con dicha grabación?

Esta entrevista puede tener una duración de 60 minutos.

Aquí tienes tu enlace personalizado de una nueva herramienta para visualizar datos antes de la matrícula de los estudiantes.

1. *Estudiante 1*
   Acceder al apartado “Administrador” y selecciona al estudiante 1.

- *Explica qué información muestra el gráfico que tienes delante. ¿Podrías describir qué significa cada color?*
- *Los valores para distribuir la visualización de asignaturas son: dificultad, popularidad, requisitos previos y solapamientos entre entregas ¿Podrías describir qué entiendes por cada uno de estos conceptos?*

  Ahora asigna los valores que crees que son más adecuados para visualizar las asignaturas:
- *¿Cómo crees que los valores afectan a la distribución de las asignaturas en el mapa?*

Haz click en "Recomendar Asignaturas"
- *¿Qué asignaturas recomienda el sistema como 3 primeras opciones?*

Habías recomendado las siguientes asignaturas:
- *En caso de no coincidir ¿Qué opinas de la recomendación que hace el sistema?*
- *¿Qué asignaturas recomendarías teniendo en cuenta la recomendación del sistema?*

Selecciona las asignaturas que crees que son más adecuadas para la matrícula de este alumno.
- *¿En qué momento del curso tendrá más entregas de actividades el estudiante?*
- *¿Cuántos días crees que el estudiante debería dedicar a cada actividad antes de entregarla?*

Indica dicho nº de días hasta la entrega en el slide
- *¿Cómo te ayuda visualizar el nº de días que se van a dedicar a cada actividad?*
- *Si has cambiado de opinión sobre las asignaturas a recomendar o su número tras utilizar esta segunda visualización justifica tu cambio de opinión.*

2. *Se realizan las mismas preguntas para 3 estudiantes más.*

3. *Datos complementarios.*
   Una vez revisada la herramienta para los 4 estudiantes, responde a las siguientes preguntas:
- *¿Qué aspectos te han gustado más?*
- *¿Qué aspectos mejorarías?*
- *¿Qué funcionalidades o elementos añadirías?*
- *¿Usarías la herramienta de visualización para hacer recomendaciones de matrícula?*
- *¿Utilizas la información de asignaturas a convalidar por el estudiante en tus recomendaciones? ¿Tendrías en cuenta las asignaturas convalidadas como factor para el recomendador? Justifica tu respuesta*
- *¿Te gustaría realizar alguna otra aportación?*

A.5 Prototype validation

The prototype validation process involved a mixed-methods approach to assess its impact on student and advisor decision making within the UOC Computer Science program. Data collection instruments included interview protocols for both students and advisors, a questionnaire specifically designed for advisors, and a heuristics evaluation template used to assess the prototype's usability. Prior to participation, data protection consent was obtained from all involved stakeholders. These documents and procedures facilitated a comprehensive evaluation of the learning dashboard's effectiveness and identified areas for potential improvement.

A.5.1 Data protection consent

The user consent was collected through a document in Spanish, using the following protocol:

DECLARACIÓN DE CONSENTIMIENTO INFORMADO. PROYECTO Supporting student's enrolment process in online learning environments by using learning-analytics based dashboards

Este documento tiene el objetivo de informarle sobre el proyecto Supporting student enrolment process in online learning environments by using learning-analytics based dashboards (en adelante, el proyecto) al que le invitamos a participar y que tiene como finalidad investigar la aplicación de tableros de aprendizaje, visualización de datos y recomendadores en el proceso de matrícula. Nuestra intención es que reciba la información correcta y suficiente para que pueda decidir si acepta o rechaza participar en el proyecto. Le rogamos que lea este documento con atención y que nos formule las dudas que tenga.

Título del proyecto: Supporting student's enrolment process in online learning environments by using learning-analytics based dashboards

Objetivo del proyecto: El objeto del proyecto es investigar la aplicación de tableros de aprendizaje, visualización de datos y recomendadores en el proceso de matrícula, lo que se pretende analizar es qué información es clave para estudiantes y tutores a la hora de tomar decisiones de matrícula en titulaciones oficiales de educación superior que permitan cierta flexibilidad y en qué medida el uso de un tablero de aprendizaje y/o un sistema recomendado es relevante para las decisiones que toman los estudiantes y tutores al momento de matricularse.

Persona responsable del proyecto: Noelia Rivas Ridruejo. Yo, el Sr. / la Sra. ______________, mayor de edad, con DNI número ______________ y dirección electrónica ____________________________, actuando en mi propio nombre y representación, mediante el presente documento, MANIFIESTO QUE HE SIDO INFORMADO/A DE LAS SIGUIENTES CUESTIONES RELACIONADAS CON EL PROYECTO:

- *Mi participación en este proyecto es voluntaria y, si en cualquier momento deseo cambiar mi decisión, puedo retirar mi consentimiento.*
- *Las personas que realizan la investigación tienen el deber de informarme de cualquier cambio en el objeto del proyecto o en la forma de participar en él, para que pueda expresar mi voluntad de seguir participando o no en el proyecto.*
- *Las personas que realizan la investigación tienen el derecho de interrumpir mi participación en el proyecto si determinan que no es adecuado que continúe participando en él, si puede ser peligroso para mí seguir participando o si no sigo las indicaciones de los investigadores para poder participar en el proyecto.*
- *Mi participación consiste en realizar una encuesta previa, una entrevista y una encuesta final. La persona responsable del tratamiento de mis datos personales es Noelia Rivas Ridruejo.*
- *Mis datos personales se recogerán y tratarán con fines exclusivamente docentes y de investigación y sin ánimo de lucro.*
- *Se captará, con los medios de grabación utilizados por la persona que lleva a cabo la investigación, mi imagen y mi voz cuando se desarrollen las actividades en las que yo participe, con el fin de realizar la investigación en el marco del proyecto.*
- *Mis datos se anonimizarán, por lo que no podrá conocerse mi identidad a partir de los datos recogidos.*
- *Se guardará secreto sobre la información personal que facilito, y solo se utilizará con fines docentes y de investigación en el marco de este proyecto, de forma que no se me pueda identificar en los resultados del proyecto. Solo se recogerán los datos mínimos que sean necesarios para llevar a cabo el proyecto (principio de minimización) y, una vez haya terminado el fin docente o de investigación que se derive de este proyecto, se destruirá de forma definitiva toda la información de carácter personal que haya facilitado.*
- *He sido informado/a mediante correo electrónico sobre el proyecto, sobre su finalidad y sobre los datos que se recogerán, y he consentido en participar en este proyecto.*

El tratamiento de los datos de carácter personal de todos los sujetos participantes se ajustará a lo dispuesto en el Reglamento General de Protección de Datos (UE) 2016/679 y a la Ley Orgánica 3/2018 de Protección de Datos Personales y Garantía de los Derechos Digitales. De acuerdo con lo establecido en esta legislación, puede ejercer los derechos de acceso, modificación, oposición, a no ser objeto de decisiones individuales automatizadas y supresión de sus datos de carácter personal dirigiéndose al responsable del tratamiento, identificado a continuación, mediante los canales de contacto establecidos.

AUTORIZO: Al Sr. / A la Sra. Noelia Rivas Ridruejo (en adelante, el responsable), con DNI número y dirección electrónica personal seosve@uoc.edu [dirección electrónica privada del responsable del proyecto], para que trate mis datos de carácter personal facilitados, para la realización de la investigación descrita en el marco del proyecto indicado. El tratamiento de estos datos se llevará a cabo según lo siguiente:

Información básica sobre protección de datos personales	
Responsable del tratamiento	*Noelia Rivas Ridruejo seosve@uoc.edu 699173517*
Fines	*Llevar a cabo las actividades de investigación detalladas en el marco del proyecto.* *Si usted nos autoriza, gestionar la autorización de uso de su imagen y utilizar el material fotográfico y audiovisual que contenga su imagen y voz en el marco del proyecto.*
Legitimación	*Consentimiento de la persona interesada.* *Consentimiento de la persona interesada para el uso de la imagen en el marco del proyecto.*
Destinatarios	*Sus datos serán utilizados únicamente por Noelia Rivas Ridruejo, y no se comunicarán a terceros sin su consentimiento, salvo en los supuestos previstos por la ley.*
Derechos de los interesados	*Podrá ejercitar su derecho de acceso, rectificación, suspensión, oposición, a no ser objeto de decisiones individuales automatizadas, portabilidad y limitación enviando un mensaje electrónico a seosve@uoc.edu y adjuntando una fotocopia del DNI o documento acreditativo de su identidad.*
Información adicional	*Puede revisar la información adicional sobre el tratamiento de los datos personales en el siguiente apartado.*

AUTORIZACIÓN PARA EL USO DE LA IMAGEN

Le informamos que, para llevar a cabo la investigación y su posterior elaboración en el marco del proyecto, se realizarán grabaciones audiovisuales de la imagen de las personas que participan en el proyecto.

Con esta autorización da permiso a Noelia Rivas Ridruejo para utilizar el material audiovisual que elabore durante el desarrollo de las actividades que formen parte del proyecto en las que usted participe y en las que aparezca su imagen y, en virtud del proyecto, su voz, durante el tiempo necesario e indispensable para la elaboración de proyecto y sin ninguna contraprestación económica.

La persona que realiza la investigación se compromete a que la utilización de estas imágenes respete la normativa aplicable y que en ningún caso suponga una intromisión ilegítima ni una vulneración de los derechos al honor, intimidad personal y propia imagen de los participantes.

☐ *Autorizo el uso de mi imagen en los términos indicados.*

Barcelona, _____ de __
El Sr. / La Sra. _____________

Información adicional sobre protección de datos personales

¿Quién es el responsable del tratamiento de los datos personales?
El tratamiento de los datos personales recogidos en el marco de su participación en el proyecto será responsabilidad de Noelia Rivas Ridruejo, con NIF y domicilio situado en Apartado de correos 78 Tudela (Navarra).

¿Con qué finalidad se tratarán los datos personales? ¿Durante cuánto tiempo?
Los datos personales recogidos mediante el presente formulario se tratarán con la finalidad de llevar a cabo el proyecto con una finalidad exclusivamente docente o de investigación y sin ánimo de lucro.

Asimismo, si usted lo ha autorizado, su imagen y voz se utilizarán para realizar grabaciones audiovisuales y fotografías en el marco del proyecto, según lo especificado en este documento.

Una vez haya finalizado la tarea o la investigación docente que se derive de la realización del proyecto, los datos personales se suprimirán de forma definitiva.

¿Cuál es la legitimación para el tratamiento de los datos?
La base legal para el tratamiento de los datos personales es el consentimiento de la persona interesada, que se podrá retirar en cualquier momento.

¿Qué medidas de seguridad se han implementado para proteger los datos personales?
Los datos personales se tratarán de forma absolutamente confidencial. Asimismo, se han implantado medidas técnicas y organizativas adecuadas para garantizar su seguridad y evitar su destrucción, pérdida, acceso o alteración ilícitos. A la hora de determinar estas medidas, se han tenido en cuenta criterios como el alcance, el contexto y las finalidades del tratamiento, el estado de la técnica y los riesgos existentes.

¿Se comunicarán los datos personales a terceros?
No se comunicarán los datos personales a terceros sin el consentimiento previo del padre/madre o los tutores legales de la persona interesada. Sin embargo, los datos personales podrán ser comunicados a terceros previstos por la ley para dar cumplimiento a las obligaciones legales que corresponda, en su caso.

¿Existen otras personas o entidades que puedan tener acceso a sus datos personales para ayudar a Noelia con alguna de las tareas relativas a las finalidades del tratamiento?
La persona responsable cuenta con el personal docente e investigador que le asiste en la ejecución de tareas relacionadas con el tratamiento de sus datos personales, concretamente, en la recogida de estos datos.

¿Cuáles son sus derechos?
Disponéis de los siguientes derechos en materia de protección de datos:

Derecho	***¿En qué consiste?***
Derecho de acceso	*Consultar de qué datos personales disponemos.*
Derecho de rectificación	*Modificar los datos personales de los que disponemos cuando sean inexactos.*
Derecho de oposición	*Solicitar que no tratemos los datos personales para algunos fines concretos, a no ser objeto de decisiones individuales automatizadas.*
Derecho de supresión	*Solicitar que eliminemos los datos personales.*
Derecho de limitación	*Solicitar que limitemos el tratamiento de los datos personales.*
Derecho a la portabilidad	*Solicitar que le entreguemos la información de que disponemos en un formato informático.*
Derecho a presentar una reclamación ante la autoridad competente	*Presentar una reclamación.* *Sin perjuicio del ejercicio de sus derechos ante el responsable del tratamiento, en cualquier momento puede presentar una reclamación ante la autoridad competente para defender sus derechos en materia de protección de datos mediante la página web https://apdcat.gencat.cat/es/inici/index.html.*

Para ejercitar estos derechos, es suficiente con que envíe una comunicación a Noelia Rivas Ridruejo por correo electrónico a la dirección seosve@uoc.edu. La solicitud deberá contener copia de su DNI o documento identificativo equivalente, así como el contenido mínimo previsto en la normativa aplicable. Si la solicitud no reúne los requisitos especificados, podremos pedirle que la subsane. El ejercicio de estos derechos es gratuito, si bien podrá cobrarse un canon cuando las solicitudes sean infundadas, excesivas o repetitivas.

A.5.2 Student preliminary questionnaire

A preliminary questionnaire, administered in Spanish, was sent before proceeding with the interviews:

¿Cómo tomas decisiones de matrícula?

Nos encontramos estudiando el proceso de matrícula de la UOC. Si necesitas más información sobre este proyecto puedes visitar: https://visualenrolment.com/es/

El motivo de este cuestionario es entender mejor cómo tomas tus decisiones de matrícula.

—-

Declaración sobre protección de datos para la recopilación de datos personales
Has sido contactado a través de tu tutor del grado de ingeniería informática. De todas formas, estamos obligados a pedir tu consentimiento de nuevo.

Lee la siguiente información atentamente y acepta el procesamiento de tus datos seleccionando la casilla "Si" si estás de acuerdo. Los datos recopilados en este formulario serán tratados de manera responsable, confidencial y destruidos al finalizar el proyecto. Si tienes dudas puedes consultar el siguiente enlace.

Los resultados del análisis de datos sólo estarán disponibles para terceros en forma de informes agregados, para que no se pueda saber quién ha contestado, ya sea de forma directa o con la ayuda de otras personas.

¿Aceptas el procesamiento de tus datos de acuerdo a lo descrito?
Si
No

—-

Te has matriculado este semestre en la UOC y queremos conocer un poco más cómo has tomado decisiones en este proceso.

1. *¿Qué número de asignaturas has matriculado y por qué?*
2. *¿Qué asignaturas has matriculado y por qué?*
3. *¿Qué información tienes en cuenta para realizar tu matrícula?*
4. *Si suspendieras una o varias asignaturas ¿Preferirías repetirlas lo antes posible o esperar un tiempo para volverlas a matricular? Explícanos por qué*
5. *¿Sigues el orden establecido en el plan de estudios? Explícanos por qué*
6. *¿Has modificado tu matrícula tras consultarla con tu tutor? Explícanos por qué*
7. *¿Tenías clara tu matrícula o valoraste diversas opciones? ¿Qué otras opciones? Explícanos por qué*
8. *¿Con qué nota puntuarías el proceso de matrícula de la UOC? (0 muy deficiente, 10 excelente, NS/NC) - Añade aquí tu valoración sobre el proceso de matrícula*
9. *¿Te gustaría añadir alguna cuestión relevante sobre tu proceso de matrícula que no te hayamos preguntado?*

A.5.3 Interview protocol

The user feedback sessions were conducted in Spanish, using the following protocol:

¡Hola! Soy Noelia Rivas, doctoranda en Tecnologías de la Información y Redes de la UOC. Muchísimas gracias por participar en esta entrevista.

Para ponerte un poco en contexto, comentarte que nos encontramos estudiando el proceso de matrícula de la UOC. Si necesitas más información sobre este proyecto puedes visitar: https://visualenrolment.com/es/

Necesitamos grabar esta entrevista para recopilar datos y transcribirla posteriormente. No te preocupes, ninguno de tus datos será publicado, aunque es posible que si se publiquen algunas de tus opiniones y apreciaciones manteniendo el anonimato. Los datos se conservarán hasta la presentación de la tesis. ¿Estás conforme con dicha grabación?

Esta entrevista puede tener una duración de 30 minutos.

Aquí tienes tu enlace personalizado de una nueva herramienta para visualizar datos de expediente y matriculación.

Estudiante

Este mapa representa tu expediente académico hasta el semestre 2022/2 incluido, sin incluir tu última matrícula.

1. *¿Identificas tu expediente académico?*
2. *¿Qué valor añadido crees que aporta el mapa?*

Estos son los valores por defecto típicos:

3. *¿Qué valores son más importantes para ti?*

Haz click en "Recomendar Asignaturas"

4. *Tú te matriculaste de N asignaturas ¿Qué asignaturas recomienda el sistema como las N primeras opciones?*
5. *Habías matriculado las siguientes asignaturas.*

En caso de no coincidir ¿Qué opinas de la recomendación que hace el sistema? / ¿Dónde están las asignaturas que matriculaste?

6. *¿Qué asignaturas hubieras seleccionado teniendo en cuenta la recomendación del sistema?*

Selecciona las asignaturas que crees que hubieran sido adecuadas para tu anterior matriculación.

7. *¿En qué momento del curso tendrás más entregas de actividades?*
8. *¿Cuántos días dedicas normalmente a preparar una entrega?*

Indica dicho nº de días hasta la entrega en el slide:

9. *Si has cambiado de opinión sobre las asignaturas a recomendar o su número tras utilizar esta segunda visualización justifica tu cambio de opinión.*

Tutor

10. *¿Estás de acuerdo con la selección? ¿Harías algún cambio?*

Una vez revisada la herramienta, responde a las siguientes preguntas:

11. *¿Os parece la herramienta un buen lugar de encuentro para tomar decisiones juntos? Justificad vuestra respuesta*
12. *¿Qué aspectos os han gustado más?*
13. *¿Qué aspectos mejoraríais?*

14. *¿Qué funcionalidades o elementos añadiríais?*
15. *¿Usaríais la herramienta de visualización para la próxima matrícula?*
16. *¿Os gustaría realizar alguna otra aportación?*

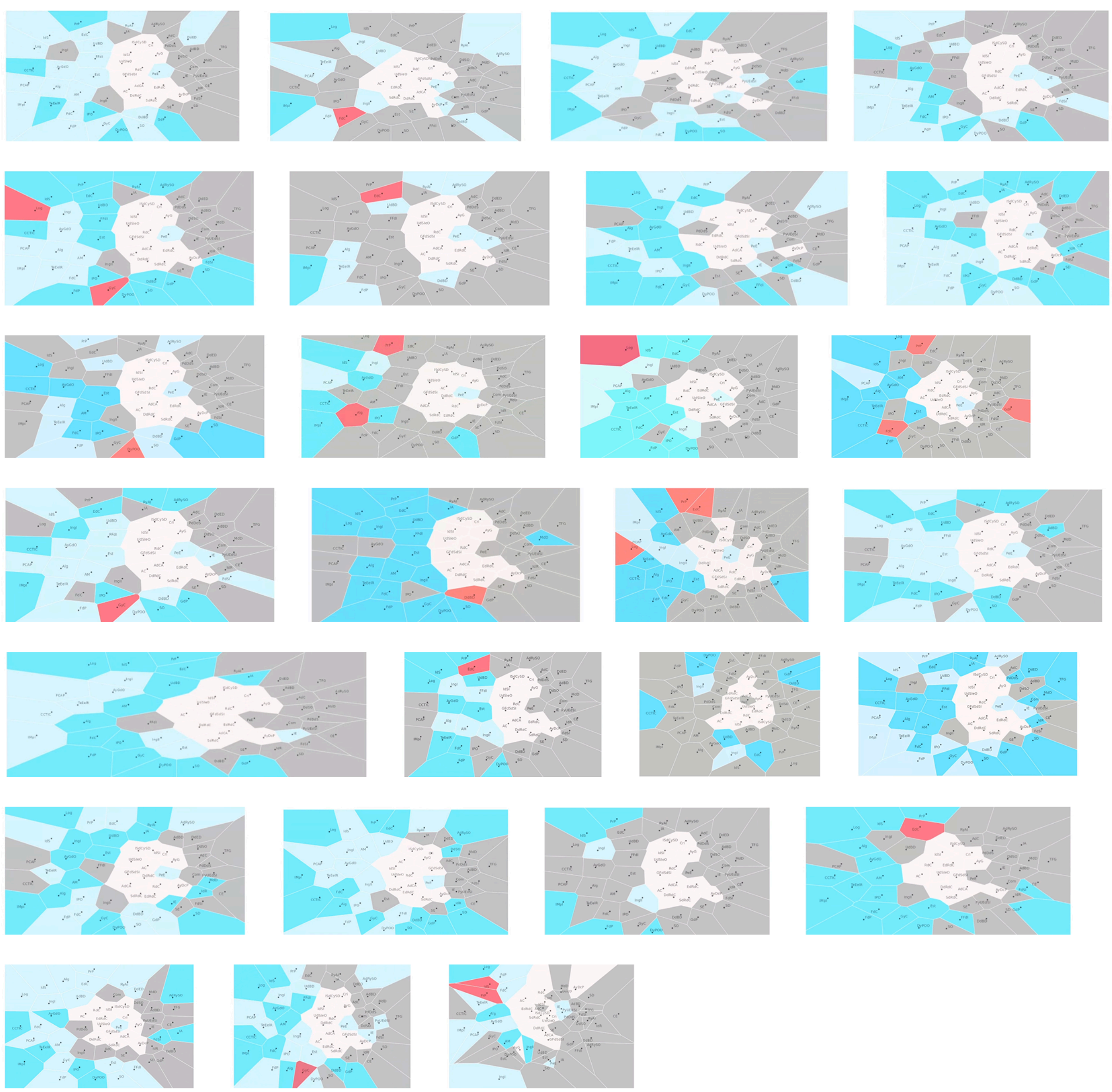
¡Muchas gracias por participar! Recordad que si estáis interesados/as en nuestra investigación podéis encontrar información sobre la misma en: https://visualenrolment.com/es/

A.5.4 Students' records generated maps

During the interviews, as each student's unique academic record was uploaded, the dashboard generated distinct visualizations reflecting the individual differences. The resulting visual representations clearly illustrated the variability across student academic paths.

Figure A.6 - Students' record maps

Examples of map visualizations created by students within the learning dashboard.



A.5.5 Student final questionnaire

A final questionnaire, administered in Spanish, was sent after the interview to the students:

PEOU
¿Te parece que la información es fácil de entender e interpretar? Explica por qué
¿Te parece una herramienta fácil o difícil de utilizar? Explica por qué

PU
¿Se mejora/facilita el proceso de toma de decisiones? Explica por qué
¿Te parece que la herramienta hace recomendaciones adecuadas? Explica por qué

A
¿Utilizarías la herramienta para el siguiente periodo de matriculación? Explica por qué
¿Qué elemento o funcionalidad te parece más relevante? Mapa, sliders, calendario, etc…
¿Seguirías contactando con tu tutor si tuvieras disponible la herramienta para decidir tu matrícula? Explica por qué

¿Con qué nota puntuarías este proceso alternativo de matrícula (incluyendo la herramienta)? (0 muy deficiente, 10 excelente, NS/NC)

Añade aspectos que consideres relevantes que no te hayamos preguntado

A.5.6 Advisor questionnaire

A questionnaire, administered in Spanish, was sent after the interview to the advisors:

PEOU
¿Te parece que la información es fácil de entender e interpretar? Explica por qué
¿Te parece una herramienta fácil o difícil de utilizar? Explica por qué

PU
¿Se mejora/facilita el proceso de toma de decisiones? Explica por qué
¿Te parece que la herramienta hace recomendaciones adecuadas? Explica por qué

A
¿Utilizarías la herramienta para el siguiente periodo de matriculación? Explica por qué
¿Qué elemento o funcionalidad te parece más relevante? Mapa, sliders, calendario, etc… Explica por qué
¿Crees que podrías hacer una propuesta de matrícula utilizando la herramienta antes de que el estudiante contacte contigo para la siguiente matrícula? Explica por qué

¿Con qué nota puntuarías este proceso alternativo de matrícula (incluyendo la herramienta)? (0 muy deficiente, 10 excelente, NS/NC)

Añade aspectos que consideres relevantes que no te hayamos preguntado

A.5.7 Heuristics template

To further validate the enrollment decision-making prototype, a heuristic evaluation was conducted with two UX experts who participated in a questionnaire based on Nielsen's ten general usability heuristics (Nielsen, 2024). This questionnaire was sent along with an explanatory video and access to the prototype. Note that the template is in Spanish.

1. *Visibilidad del estado del sistema*

Nº	***Pregunta***	***Si / No / NSNC***	***Comentarios***
1.1	*¿Cada visualización comienza con un título o encabezado que describe el contenido de la pantalla?*		
1.2	*¿Existen indicadores para cada acción?*		
1.3	*Después de que el usuario completa una acción (o grupo de acciones), ¿se indica que se puede iniciar la siguiente acción?*		
1.4	*¿Hay información visual en los menús sobre qué opciones se pueden seleccionar?*		
1.5	*¿Hay información visual sobre qué opciones ya están seleccionadas?*		
1.6	*Al mirar, ¿El usuario puede saber el estado del sistema y las alternativas de acción?*		

2. *Coincidencia entre el sistema y el mundo real*

Nº	***Pregunta***	***Si / No / NSNC***	***Comentarios***
2.1	*¿Las opciones del menú están ordenadas de la forma más lógica, teniendo en cuenta el usuario, los nombres de los elementos y las variables de cada una de las tareas?*		
2.2	*¿Se ha utilizado una secuencia lógica para las opciones del menú?*		
2.3	*¿Los colores seleccionados corresponden a las expectativas comunes sobre los códigos de color?*		
2.4	*¿Las tareas se describen con terminología familiar para los usuarios?*		

3. *Control y libertad del usuario*

Nº	***Pregunta***	***Si / No / NSNC***	***Comentarios***
3.1	*¿Existe una función "deshacer" a nivel acción o grupo de acciones?*		
3.2	*¿Pueden los usuarios cancelarlas acciones en curso?*		
3.3	*¿Existe algún mecanismo que permita a los usuarios volver a las acciones anteriores?*		

4. *Consistencia y estándares*

Nº	***Pregunta***	***Si / No / NSNC***	***Comentarios***
4.1	*¿La estructura del menú coincide con la estructura de las tareas?*		
4.2	*¿Se han establecido estándares de la industria o la empresa para el diseño de menús y se aplican de manera consistente en todas las pantallas de menú?*		
4.3	*¿Se utilizan con cuidado las técnicas de llamada a la acción?*		
4.4	*¿Se proporciona una leyenda si los códigos de color son numerosos o su significado no es obvio?*		
4.5	*¿Las acciones a realizar por el usuario se nombran de manera consistente en todos los textos de la herramienta?*		

5. *Prevención de errores*

Nº	***Pregunta***	***Si / No / NSNC***	***Comentarios***
5.1	*¿Las opciones de menú son lógicas, distintivas y mutuamente excluyentes?*		
5.2	*¿Evita la herramienta que los usuarios cometan errores siempre que sea posible?*		

6. *Reconocimiento en lugar de recuerdo*

Nº	***Pregunta***	***Si / No / NSNC***	***Comentarios***
6.1	*¿Se muestran todos los datos que un usuario necesita en cada paso de una secuencia de acciones?*		
6.2	*¿Se colocan indicaciones y mensajes donde es probable que se mire en la pantalla?*		
6.3	*¿Las áreas de texto tienen márgenes a su alrededor?*		
6.4	*¿Se han agrupado los elementos en zonas lógicas y se han utilizado encabezados para distinguir entre zonas?*		
6.5	*¿Se han separado las zonas por espacios, líneas, colores, letras, títulos en negrita, líneas de reglas o áreas sombreadas?*		
6.6	*¿La codificación de colores es consistente en toda la herramienta?*		
6.7	*¿Existe un buen contraste de color y brillo entre la imagen y los colores de fondo?*		
6.8	*¿Los elementos del menú inactivos están atenuados o se omiten?*		

7. *Flexibilidad y eficiencia de uso*

Nº	***Pregunta***	***Si / No / NSNC***	***Comentarios***
7.1	*Si el sistema admite usuarios tanto principiantes como expertos, ¿Hay disponibles varios niveles de detalle según el tipo de usuario?*		
7.2	*¿Se personaliza el contenido y las funcionalidades para cada usuario?*		
7.3	*¿Los usuarios pueden realizar sus propias selecciones para que la herramienta se adapte a sus necesidades?*		

8. *Diseño estético y minimalista*

Nº	***Pregunta***	***Si / No / NSNC***	***Comentarios***
8.1	*¿Se muestra en la pantalla sólo (y toda) la información esencial para la toma de decisiones?*		
8.2	*¿Tiene cada pantalla de entrada de datos un título breve, sencillo, claro y distintivo?*		
8.3	*¿Las etiquetas de los campos son breves, familiares y descriptivas?*		
8.4	*¿Las indicaciones se expresan afirmativamente y utilizan la voz activa?*		
8.5	*¿Los títulos de los menús son breves pero lo suficientemente largos para comunicar?*		
8.6	*¿Hay menús emergentes o desplegables dentro de los campos de entrada de datos que tengan muchas opciones de entrada, pero bien definidas?*		

9. *Ayudar a los usuarios a reconocer, diagnosticar y recuperarse de errores*

Nº	***Pregunta***	***Si / No / NSNC***	***Comentarios***
9.1	*¿Las indicaciones se expresan de manera constructiva, sin críticas abiertas o implícitas al usuario?*		
9.2	*¿Las indicaciones implican que el usuario tiene el control?*		
9.3	*¿Las indicaciones breves e inequívocas?*		
9.4	*¿Los mensajes dan a los usuarios el control del sistema?*		

10. Ayuda y documentación

Nº	*Pregunta*	*Si / No / NSNC*	*Comentarios*
10.1	*¿Las instrucciones son visualmente distintas?*		
10.2	*¿Las instrucciones siguen la secuencia de acciones del usuario?*		
10.3	*Si las opciones del menú son ambiguas, ¿la herramienta proporciona información explicativa adicional cuando se selecciona un elemento?*		
10.4	*¿La interfaz de la herramienta de ayuda (navegación, presentación) es coherente con las interfaces de navegación y presentación?*		
10.5	*Navegación: ¿Es fácil encontrar la información?*		
10.6	*Presentación: ¿Está bien diseñada la herramienta?*		
10.7	*La información que proporciona, ¿Es relevante?*		
10.8	*¿Entiende el usuario qué puede hacer con la herramienta?*		
10.9	*¿Entiende el usuario para qué se utiliza la herramienta?*		
10.10	*¿Entiende el usuario cómo se utiliza la herramienta?*		
10.11	*¿Entiende el usuario por qué utilizar la herramienta?*		
10.12	*¿Entiende el usuario en qué punto está dentro de la herramienta?*		

A.5.8 First expert answers

1. *Visibilidad del estado del sistema*

Nº	*Si / No / NSNC*	*Comentarios*
1.1	*No*	*Sí que existe un título para los contenidos específicos, pero falta un título general de la herramienta (a no ser que se trate de Visual Enrolment, que en este caso debería ganar visibilidad)*
1.2	*Sí*	
1.3	*A veces*	*Falta relación entre la acción de "Escull un estudiant" y la información mostrada en "El teu expedient". Aunque están relacionadas a nivel de datos, el usuario no selecciona el estudiante en una pestaña y ve el expediente en otra, sin que exista ningún indicador a nivel de interfaz.*
1.4	*Sí*	
1.5	*Sí*	
1.6	*A veces*	*En el "Recomanador d'assignatures" o existen indicaciones sobre qué acciones pueden realizarse sobre el mapa.*

2. *Coincidencia entre el sistema y el mundo real*

Nº	*Si / No / NSNC*	*Comentarios*
2.1	*No*	*Interpreto que lo que elegimos en Configuració determina el resto de datos. En cambio, esta opción se encuentra en último lugar. SI lo he interpretado correctamente, deberíamos configurar en primer lugar, e interactuar con el resto de la plataforma después.*
2.2	*No*	*(ver comentario 2.1)* *Además, las opciones de configuración del recomendador están en la pantalla Configuración; sería más intuitivo que estuvieran en la misma pantalla del recomendador)*
2.3	*Sí*	*Comentario adicional respecto al mapa: creo que el juego rojo / azul (no suprada / superada) puede ser menos intuitivo que rojo / verde para los mismos valores.*
2.4	*Sí*	*Comentario adicional: las instrucciones del panel izquierdo (fondo gris) resultan largas y complejas. Sugiero simplificar la redacción.*

3. *Control y libertad del usuario*

Nº	*Si / No / NSNC*	*Comentarios*
3.1	*No*	*No es necesario, porque no existe una acción crítica*
3.2	*No*	*No existen acciones que impliquen un tiempo cancelable*
3.3	*No*	*No creo que sea necesario: todo es reconfigurable*

4. *Consistencia y estándares*

Nº	***Si / No / NSNC***	***Comentarios***
4.1	*No*	*(ver comentario 2.1)*
4.2	*No*	*Aunque en general es todo correcto, el hecho de que el mapa de la izquierda esté siempre presente causa confusión, ya que en realidad permite gestionar la visualización en mapa. Sugerencia: incluir el panel solamente en la pestaña “Recomanador d’assignatures”*
4.3	*Sí*	
4.4	*Sí*	
4.5	*Sí*	

5. *Prevención de errores*

Nº	***Si / No / NSNC***	***Comentarios***
5.1	*Sí*	
5.2	*Sí*	

6. *Reconocimiento en lugar de recuerdo*

Nº	***Si / No / NSNC***	***Comentarios***
6.1	*No*	*Los datos de configuración quedan ocultos bajo la pestaña correspondiente. Creo que sería óptimo tener permanentemente visibles los esenciales (grado, semestre, estudiante), ya que interpreto que gobiernan sobre todo lo que estamos viendo en el resto de pantallas de la herramienta.*
6.2	*Sí*	
6.3	*Sí*	
6.4	*No*	*El formulario de Configuración tiene dos grupos de opciones (las relativas al recomendador y las de estudios) que no se diferencian entre sí*
6.5	*Sí*	
6.6	*Sí*	
6.7	*Sí*	
6.8	*Sí*	

7. *Flexibilidad y eficiencia de uso*

Nº	***Si / No / NSNC***	***Comentarios***
7.1	*No*	
7.2	*No*	*Se personalizan los datos según las selecciones del usuario, pero no la interfaz*
7.3	*Sí*	

8. *Diseño estético y minimalista*

Nº	***Si / No / NSNC***	***Comentarios***
8.1	*No*	*Las opciones de configuración del recomendador están en la pantalla Configuración; sería más intuitivo que estuvieran en la misma pantalla del recomendador*
8.2	*Sí*	
8.3	*Sí*	*Comentario adicional: el texto del panel izquierdo resulta muy largo y complejo.*
8.4	*Sí*	
8.5	*Sí*	*Ver comentario 8.3*
8.6	*No*	

9. *Ayudar a los usuarios a reconocer, diagnosticar y recuperarse de errores*

Nº	***Si / No / NSNC***	***Comentarios***
9.1	*Sí*	*Ver comentario 8.3*
9.2	*Sí*	
9.3	*Sí*	*Ver comentario 8.3*
9.4	*Sí*	

10. Ayuda y documentación

Nº	***Si / No / NSNC***	***Comentarios***
10.1	*Sí*	
10.2	*Sí*	
10.3	*No*	*Hay un icono “i” en las opciones del panel izquierdo, pero no parece funcionar*
10.4	*Sí*	
10.5	*Sí*	
10.6	*Sí*	
10.7	*Sí*	
10.8	*No*	*Al acceder a la herramienta no se tiene clara la secuencia de acciones. Sugerencia: incluir unas breves instrucciones en la primera pantalla*
10.9	*Sí*	*Lo entiende a medida que la utiliza (no de entrada)*
10.10	*Sí*	*Lo entiende a medida que la utiliza (no de entrada)*
10.11	*Sí*	*Lo entiende a medida que la utiliza (no de entrada)*
10.12	*Sí*	

A.5.8 Second expert answers

1. *Visibilidad del estado del sistema*

Nº	***Si / No / NSNC***	***Comentarios***
1.1	*Sí*	*No obstante, el título “Mapa de asignaturas” debería tener como mínimo el mismo tamaño que “Calendario de entrega de actividades”*
1.2	*Sí*	*En la caja izquierda con el botón “Siguiente”, con la que tengo sensaciones encontradas: por un lado, es clara en su lugar y cantidad de texto (con algunos copies como indicar que el descarte es opcional podría decirse antes). Por otro, me parece que cada paso podría tener un icono u otro elemento visual en esa caja que cambiara, o una especie de estatus bar, para que sea más evidente que van modificándose las intrucciones.*
1.3	*Sí*	
1.4	*Sí*	*Si los pasos 1-4 tuvieran flechitas a lo breadcrumbs creo que sería más claro visualmente que es un proceso / secuencia de pasos.*
1.5	*No del todo*	*Ver comentario 2.3*
1.6	*Depende*	*Lo que indico en comentarios 1.2, 1.4, 3.3 por ekemplo podría confundir sus opciones de interacción a medida que avanza.*

2. *Coincidencia entre el sistema y el mundo real*

Nº	***Si / No / NSNC***	***Comentarios***
2.1	*Sí*	*Creo que el menú desplegable en el paso 3 de destacar asignaturas, muy útil, debería ser mejor como un checkbok o botonera que permita tener todas las opciones a la vista (que si no me equicovo con siempre 10: Básica, Obligatioria, etc).*
2.2	*Sí*	
2.3	*No exactamente*	*Me parece claro cuando se activan los tonos de verde en la viz en el paso 3 (aunque creo es cuando deberían aparecer en la leyenda izquierda los códigos de ese color, y no desde el principio con R1, R2, etc). Pero luego en el paso 4 encuentro más problemático que se salte a otro código de color (azul oscuro). Entiendo aunque más complejo de programar lo suyo sería que se mantengan los colores y se indicara con malla de franjas blancas o rayado, etc sobre el mismo color de origen (para mayor consistencia cromática).*
2.4	*Sí*	*Está el tema de si un lenguajemás ambiguo entre “tú” (user: estudiante) y “el estudiante” (user: tutor de matrícula) podría ser lo más conveniente para el uso generalizado de la herramienta.*

3. *Control y libertad del usuario*

Nº	*Si / No / NSNC*	*Comentarios*
3.1	*No exactamente*	*Pero la opción "Anterior" cumple esa función (con un símbolo o elemento del estilo < se haría más evidente no obstante)*
3.2	*No*	*Tampoco sirve diría recargar la página o los botones superiores del nabegador, que es algo instintivo para muches usuaries.*
3.3	*No del todo*	*Esta es un punto importante: no se puede rebobinar a la "bread crumbs" entre los pasos 1 > 2 > 3 > 4 (solo la opción "Anterior", menos visible)*

4. *Consistencia y estándares*

Nº	*Si / No / NSNC*	*Comentarios*
4.1	*Sí*	
4.2	*Casi siempre*	*Ver detalles de navegador en comentario 3.2*
4.3	*Demasiado*	*En el sentido que como voy comentando se pòdría a mi entender enfatizar más gràficamente algunas de las indicaciones u opciones de navegación, de masiado homogéneas en general.*
4.4	*No!*	*Bug importante: Tanto en Firefox como en Chrome y Opera las cajas flotantes de información detallada de asignaturas al hacer "roll over" en la visualización principal no se muestran en la pantalla, solo se ve sesgadamente a la derecha (se adjunta captura). A no ser que sea un tema de Ubuntu claro :(*
4.5	*Sí*	

5. *Prevención de errores*

Nº	*Si / No / NSNC*	*Comentarios*
5.1	*Sí*	
5.2	*Bastante*	*Tal vez el reminder de que no es una selección si no una sugerencia de matrícula sea importante para algún tipo de estudiante que desconozca el proceso, pero entiendo eso excede el diseño actual y es de una instancia superior.*

6. Reconocimiento en lugar de recuerdo

Nº	**Si / No / NSNC**	**Comentarios**
6.1	*No siempre*	*Debido a lo que comento en 4.4 en cuanto a la caja flotante de + info asignaturas. Otro bug importante aquí creo, en el paso final de selección también, es que si se especifica más de 20 días de dedicacuión estimada, el calendario peta con el error: "An error has occurred. Check your logs or contact the app author for clarification" (se adjunta captura).*
6.2	*No siempre*	*Ver comentario 4.4*
6.3	*Sí*	
6.4	*Sí*	*No obstante, el principio mencionado de "a mayor distancia entre asignaturas en la viz, menos matricularse juntas" a medida que se ecualizan los cuatro criterios en el paso 2, no sé si queda del todo claro o se podría enfativar más de alguna manera informativa (o visual simple). Creo que es la principal mejora pendiente a nivel conceptual o de base de la viz en las interacciones que he ido testeando.*
6.5	*Sí*	
6.6	*Sí*	*Mejorable tal vez como comento en 2.3*
6.7	*Sí*	
6.8	*Sí*	

7. Flexibilidad y eficiencia de uso

Nº	**Si / No / NSNC**	**Comentarios**
7.1	*No*	
7.2	*Sí*	*A medida que se avanza, se va acotando como función principal de la herramienta.*
7.3	*Sí*	*Otra parte del "core" y que cumple su objetivo.*

8. Diseño estético y minimalista

Nº	**Si / No / NSNC**	**Comentarios**
8.1	*No del todo*	*Nuevamente por lo que comento en 4.4*
8.2	*Sí*	
8.3	*Sí*	
8.4	*Sí*	
8.5	*Sí*	
8.6	*NSNC*	*Creo no aplica, pero sí conecta con que las pestañas "Recomendador | Tu expediente | Configuración" no son muy intuitivas o atractivas al click, se sobre entiende son secundarias o previas, en mi percepción.*

9. *Ayudar a los usuarios a reconocer, diagnosticar y recuperarse de errores*

Nº	***Si / No / NSNC***	***Comentarios***
9.1	*Sí*	
9.2	*Sí*	
9.3	*Sí*	
9.4	*Sí*	

10. *Ayuda y documentación*

Nº	***Si / No / NSNC***	***Comentarios***
10.1	*Sí*	
10.2	*Sí*	
10.3	*Sí*	*Aunque el estandard de “i” con mouseover oara cada definir cada criterio del paso 2 no sé si es la mejor solución, dado que el texto emergente es muy breve tal vez podría estar más explícita.*
10.4	*Sí*	*Escepto lo que comento arriba como una potencial mejora.*
10.5	*Sí*	*Excepto el issue con la caja de texto flotante con info sobre asignaturas on mouse over, que no me ha permitido checkear ese tipo de contenido.*
10.6	*Sí*	
10.7	*Sí*	*Creo es una contribución muy buena y sólida, pese a comentar principalmente los temas mejorables aquí. Tiene además ese elemento de entretenimento y combinatorias constructivas, para resolver dudas d’usuarie.*
10.8	*Sí*	*Echo a faltar tal vez el poder de una metáfora visual. Tipo (en plan brainstorming aquñí: el paso inicial del mapa recomponiéndose es la cima de una montaña, se llega recorriendo los territorios adyacentes que se agrupan, los azules de cada calendario com una especie de mapa de precipitaciones o de previsión climatológica durante el trayecto, etc.*
10.9	*Sí*	*Otro tema menor que supongo excede el diseño necesario: el final del proceso cuando se salta a la página de resultados es puro texto mínimamente maquetado (“Gracias por utilizar Visual Enrollment!” etc) y leugo al descartar el PDF es un pantallazo de lo mismo. Para su aplicación en real habría que trabajar eso, recuperar gráficos ahí etc.*
10.10	*Sí*	*Excepto por issues menores comentados, más los dos críticos identificados en 4.4 y 6.1*
10.11	*Sí*	
10.12	*Sí, mayormente*	