Learning about Learning: Unravelling Interactions in Higher Education with Learning Analytics

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Abstract

Learning is a multidimensional process that evolves and changes, influenced and affected by several elements. The sudden shift in teaching modality when the pandemic hit implied changes in social interactions, digital platforms use, and collaboration dynamics; potentially impacting the students' learning experience.

This research, initially motivated by the unknown effect of the pandemic on teaching and learning practices, lies on the grounds of the Learning Analytics (LA) research field, focused on analysing and understanding learning processes and the environments in which they occur. The dissertation takes the standpoint of interactions with the aim of furthering our understanding of how different types of interactions occurring in higher education inform and relate to students' learning strategies and behaviours. In this dissertation, quantitative and qualitative approaches, as well as a variety of data sources, are used to explore the research question: *How and to what extent can the analysis of interactions be used to inform features and changes in undergraduates' learning strategies and behaviours?* In educational contexts, interactions correspond to the various ways of communication and engagement that occur between learners, instructors, learning material, and technology. The dissertation thereby presents five chapters focused on exploring several interaction types in the context of higher education, including interactions between humans (student, instructor) and systems (digital ecosystem, content).

The results presented in the chapters provide insights into the presence and evolution of study profiles, the relationship between usage of digital platforms and resources, assignment solving, and academic performance, the effect of a data-driven intervention of class schedules and its effect on students' learning activity and experiences, the design and adoption of an institutional programme for supporting instructors, as well as insights on the dynamics of discussion forum interactions in different teaching modalities, and their value and limitations for informing the identification of students at risk of failing.

Three main contributions are highlighted in this dissertation. Firstly, by analysing different types of interactions in higher education, the dissertation provides an overview of how these interactions influence each other as well as their relationship with students' learning strategies and behaviours. Furthermore, these insights are helpful for informing the development and adoption of

LA research on interactions, which are illustrated in a conceptual framework integrating the dissertation findings, implications and recommendations. Secondly, the dissertation contributes to addressing shortcomings of LA research. It provides insights into students' behaviours and strategies, interactions, learning material usage, course improvements, and interventions in educational settings. Furthermore, practical recommendations in regards to data, resources, and support are provided. Finally, by taking into consideration students, instructors, and digital ecosystems, the dissertation offers insights into the effect of the pandemic on teaching and learning practices in higher education.

Keywords / Efnisord: learning analytics, interactions, higher education

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I heard once that doing a PhD is a journey that you need to complete alone. However, from my experience, although a PhD journey is something you need to do by yourself, you are never alone. I was not. The more I look back on my journey, the more thankful I am for the many people who have helped me grow personally and academically. Their support, encouragement, and advice have been key in making this journey possible. I would like to start by thanking my beloved supervisors, for their amazing guidance and support.

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Publication list

Publications included in the dissertation

Chapter 4: Exploring Study Profiles of Computer Science Students with Social Network Analysis

N. López Flores, A. S. Islind, and M. Óskarsdóttir, "Exploring study profiles of computer science students with social network analysis," in *The 55th Hawaii International Conference on System Sciences (HICSS)*, ser. The 55th Hawaii International Conference on System Sciences (HICSS), Jan. 2022. DOI: 10.24251/HICSS.2022.214

Chapter 5: Making the Most of Slides and Lecture Captures for Better Performance: A Learning Analytics Case Study in Higher Education

N. G. López Flores, A. S. Islind, and M. Óskarsdóttir, "Making the most of slides and lecture captures for better performance: A learning analytics case study in higher education," in *The 56th Hawaii International Conference on System Sciences (HICSS)*, Jan. 2023, pp. 1291–1300. DOI: 10.24251/HICSS.2023.159

Chapter 6: A Learning Analytics Driven Intervention to Support Students' Learning Activity and Experiences

N. López Flores, A. S. Islind, and M. Óskarsdóttir, "Digitalization and digital competence in educational contexts," in Routledge, Dec. 2023, ch. A learning analytics-driven intervention to support students' learning activity and experiences, pp. 81–102, ISBN: 978-1-00-335569-4. DOI: 10.4324/9781003355694-10

Chapter 7: Supporting Teachers in Higher Education: Design of an Institutional Programme from a Socio-technical Perspective

N. G. López Flores, M. Óskarsdóttir, and A. S. Islind, "Supporting teachers in higher education: Design of an institutional programme from a socio-technical perspective," *Frontiers in Education*, (Year), in submission

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Chapter 8: Socio-temporal insights on online discussion forum interactions

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Chapter 1

Introduction

> *"Por eso la educación es tan poderosa, porque te enseña a arrebatar lo que la vida te niega, te enseña a arrebatar lo que tu mereces y te enseña a romper tus propios miedos"*
>
> — Eufrosina Cruz Mendoza

> *"That's why education is so powerful, because it teaches you to snatch away what life denies you, it teaches you to snatch away what you deserve, and it teaches you to break through your own fears."*
>
> — Eufrosina Cruz Mendoza

Throughout the course of the past few decades, technology advancements have made a huge impact on various aspects of our lives. Such advancements have not only benefited the development of new methods, but also, have facilitated the availability and adoption of such resources by the general public [26]. This increase on the technology adoption and the wide spread of digital technology-based tools, applications, and systems also favoured an increase in the generation and availability of data [27].

In the recent years, such availability also benefited the conceptualisation of analytics as an opportunity for improving our understanding of real-world processes. The analysis of these data gained increased attention, shedding light on the application of new methodologies, addressing new problems, and uncovering new knowledge and insights [28]. The list of examples is extensive, including applications in multiple fields, such as healthcare, education, and finance (e.g. [29]–[31]).

Likewise, in education the increased use of digital technology-based resources, also increased the possibilities in terms of data analysis. Firstly by the availability of data, which is generated by multiple means (log activity, users' actions, and systems' data) [31]. Every activity session involves a series of actions that are recorded into the system, including views, clicks, navigation across different system's elements, and files downloads and uploads [32]. And secondly, by the development and adoption of resources to support and enhance teaching and learning [31]. These resources include all kinds of tools and systems, ranging from basic clickers that allow the students to take part in class dynamics favouring engagement and involvement [33], to learning management systems and digital learning environments, to facilitate the provision of resources [34], to the recent development of artificial intelligence applications, that not only enlarged the capabilities in terms of teaching and learning, but also exacerbated the need for policies and guidelines [35]. The development of such resources, the analysis of the data generated by their use, and the insights about learning processes obtained favoured the development of learning analytics as an impactful research field.

1.1 Learning analytics

The field of Learning Analytics (LA) was initially conceptualised in the early 2010's as the "measurement, collection, analysis, and reporting of the data about learners and their contexts, for purposes of understanding and optimising learning and the environments in which it occurs" [32]. Throughout its history, the field has evolved into a cross-disciplinary research domain in which educational sciences, psychology, pedagogy, data science, and computer science collaborate to shed light on learning processes.

The context in which LA takes place is complex, involving multiple elements, methodologies, stakeholders, and objectives. In 2015, a few years after its establishment, Khalil and Ebner [36] introduced the LA life cycle (Figure 1.1). The cycle includes four main elements, learning environment, big data, analytics, and act. In the first element, learning environment, stakeholders involved in education (and the data generated) are included: learners, instructors, educational institutions, administrators, and researchers. The second element, big data, includes data sets from multiple sources reflecting different behaviours and features, for example system logs and traces, personal data, academic information, etc. Quantitative and qualitative methods are included in the third element, analytics. As with the conceptualisation of the field, the range of methods adopted to analyse data from educational settings has also evolved. Finally, act, refers to the objectives sought to be fulfilled with LA research. Examples of such objectives are prediction, recommendation, intervention design, personalisation, and optimisation.

The field has evolved considerably over the years, encompassing not only

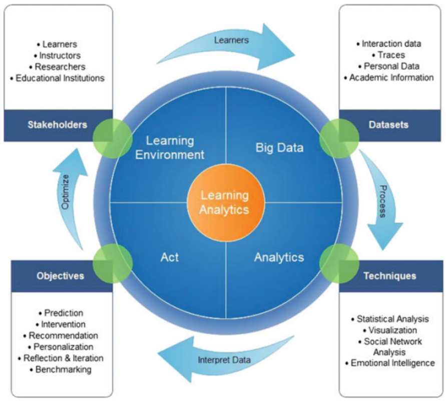


Figure 1.1: Learning analytics cycle defined by Khalil and Ebner [36].

data collection, analysis, and optimisation as it was in its initial definition, but also concerns and opportunities, establishing itself as a global research domain [37].

Constraints, limitations and challenges

Along with the development of the field, challenges and limitations on adoption, generalisation, and explainability have also been clearly identified.

LA researchers have recognised the constraints and limitations in the analyses and methods implemented. Methodological limitations, for instance, relate to the lack of longitudinal analyses, small sample sizes, and the limited number of data sources used [38]–[40]. On the practical side, the biggest limitations are related to the generalisation of the results to broader contexts and the adoption of LA in educational institutions [41], [42]. Furthermore, constraints on the interplay between privacy, ethics, security, transparency, and usability along with the lack or adequate regulation or policies on data protection and ownership have been acknowledged by the LA community [36], [37].

One of the biggest challenges for LA research is that it is developing faster than it is being adopted, which also constitutes one of its biggest limitations [43]. For instance, methodological advances have favoured the development of complex models capable of processing vast amounts of data and identifying students at risk with high accuracy, as well as the creation of dashboards to inform instructors and students. However, despite these advancements, successful implementation of such detection models and dashboards, and the translation of LA research outcomes into practical improvements remain limited [38]. To favour the adoption of LA research, there is a significant need to broaden the existing literature providing evidence of its implementation's impact on learning [44].

The reasons for such limitations are varied. Although big data analytics is undoubtedly a powerful approach to analyse large amounts of data, extract value, and transform information into knowledge and insights that enlighten several aspects of teaching and learning, not all data that comes from educational settings is necessarily big data. In many contexts, the data generated is small, biased, and limited. Nonetheless, LA should not be only about big data, as small data sets, containing a limited number of data points or features, also have the potential to offer unique and valuable perspectives about the specific learning context they belong to.

Although limitations related to data could be mostly classified as technological or interface challenges for the institutional LA adoption, in practice, data limitations can also be linked to pedagogical, leadership, and ethical challenges [44]. The technological and interface challenges arise when data is limited or unavailable, databases are incompatible, data literacy is low, analytical tools are complex, or the contextualisation and customisation of data is lacking. In contrast, pedagogical, leadership, and ethical challenges are comprised of the use of divergent learning technologies resulting in limited or inaccessible data, the lack of data governance structure in the institution, as well as privacy, ownership, and transparency concerns related to the use of the data generated [44]. In regard to data, attention has also been expanded beyond concerns about the limited or inaccessible existing data, to the evaluation of means for facilitating the collection of better data from educational contexts [37].

In regard to generalisation, limitations and challenges relate to the difficulty of extending previous research results to settings that are different from the context in which the research was conducted. Not only does this limit the adoption of LA, but it also calls for studies to replicate and validate these findings in specific settings as well. Considering that there is no such thing as a one-size-fits-all solution in LA research, it is critical to investigate all the elements associated with such variations in results under different conditions. Elements that have been found to influence the generalisation of findings include teaching modality[42] and assessment structure [45].

Thus, considering both challenges and limitations on generalisation and adoption, the implementation and adoption of LA in educational institutions requires not only technical and analytical expertise, but also a deep understanding of the institutional culture shaping the behaviour and interactions encountered [44].

Additional challenges and limitations have been encountered with the development of comprehensive, complex, and accurate models to describe learning-related elements. For example, complex models may provide accurate predictions (e.g. students at risk of failing, learning outcomes, etc.), but they are often difficult to interpret [46]. In consequence, their complexity not only limits the extent to which they can be used to inform actionable recommendations to prevent failure or enhance learning, but also, the lack of interpretability (i.e. the transparency of the internal mechanics of a model) and explainability (i.e. the ability to provide understandable reasons for the model's decisions) may result in a lack of confidence in the models decision-making process. Models' explainability and interpretability are necessary to guarantee their trustworthiness, fairness, and ethical use [47], [48].

Moreover, such limitations became more evident and were further intensified since 2019 when the COVID-19 pandemic hit. With the outbreak of the COVID-19 pandemic, the educational system around the world was turned upside down, impacting education in several ways [49]. On the one hand, the change in the conditions in which education was provided during the pandemic involved the physical location of students and teachers, who had to quickly adapt to an online learning setting in a matter of days in most countries, limiting the social interactions to the online environment. On the other hand, the physical distance imposed also modified the way in which communication and educational resources were delivered. Some of the needs were addressed by adopting new digital tools and platforms for communication, whereas other needs were addressed by adapting digital platforms previously used [50], [51]. In consequence, changes in digital platforms and educational resources modified the way instructors and students interacted with the digital platforms and educational resources provided.

1.2 Motivation and research focus

This research project started in 2020 in the light of the COVID-19 pandemic and all the changes it implied for education. At the time, questions arose in regard to its effect over teaching, learning, and the use of the educational systems. Multiple concerns were raised at the time, from technological limitations, to students engagement, motivation, or the long term effects of the pandemic and the sudden swift to online teaching and learning.

The initial objective was then set to understand "how did the usage of the systems change?". To do so, the first approach, after the first 'pandemic' term (Spring 2020), was to explore the teachers' perception of such changes. A series of semi-structured interviews were conducted with professors at the Computer Science Department at Reykjavik University. In this interview, the professors were asked to describe what changes in the use of digital technology, platforms and resources, as well as changes in the students' participation and academic performance they noticed since the pandemic started. Along with concerns related to the lack of direct contact, lower levels of participation and engagement, and modifications in the use of digital technology, the professors agreed that such change had a direct impact on their (students and teachers) experience. As expressed by one of the interviewees:

> “I have noticed basically, less involvement among students. And this can be expressed itself in the terms of interaction [...] They don’t work in groups at all. All eight students submit all the assignments separately, which shows that they are now functioning very differently from before, they’re not interacting between themselves. And this is the big concern, [...] if we don’t do anything explicit, we’re going to be seeing even more of this isolation. And therefore, isolation also means like, like I said, less engagement, less involvement.”

The sudden shift in the teaching modality when the pandemic hit implied changes in multiple elements related to learning activities, including in person social interactions between students and instructors, the digital platforms used for the delivery of course content in lectures and practical sessions, and the interaction dynamics for collaboration and communication. In person interactions were significantly reduced in the most critical period during the pandemic outbreak, limiting the social interactions to online means. This shift led to a greater reliance on digital platforms, favouring the emergence of alternative ways of facilitating communication and collaboration between students and instructors, and therefore impacting the classroom dynamics, the way learning resources were delivered, and potentially the students’ learning experience.

These changes on the dynamics of education delivery motivated the exploration of these elements from the standpoint of interactions in order to enhance our comprehension of their influence and relationship with the students’ learning behaviours.

My research focus is therefore on understanding how interactions relate to students’ learning strategies and behaviour. The dissertation thereby presents five chapters focused on exploring several interaction types in the context of higher education, including interactions between humans (student, instructor) and systems (digital ecosystem, content). These chapters not only focus on exploring specific interactions, but also encompass different data sets and research methods according to the interaction type being investigated. Accordingly, each chapter holds its own research questions and objectives, focused on exploring their specific type of interactions and learning behaviours or elements. As a whole, these chapters are linked by the overarching question running throughout this dissertation:

> *How and to what extent can the analysis of interactions be used to inform features and changes in undergraduates' learning strategies and behaviours?*

Furthermore, it is important to acknowledge the role of the COVID-19 pandemic in the development of this research. In particular, this dissertation also provides a comprehensive exploration of interactions that occurred prior to, during, and following the outbreak of the COVID-19 pandemic.

1.3 Outline and contributions

This dissertation focuses on examining interactions in higher education, and the extent to which they can inform on learning strategies and behaviours. This section presents the general outline of the dissertation and highlights the objective, main results, and contributions of each chapter. On the whole, each chapter contributes to a broader picture of how, when, and why interactions happen in higher education. Presented in Figure 1.2 is an overview of all the interactions discussed in this dissertation, accompanied by the corresponding chapter(s) addressing them.

Chapter 1

The current chapter provides an overview of the field of LA as well as the challenges and limitations it has encountered since its emergence. It also outlines the motivation and research focus, along with a general overview of the chapters included in the dissertation, the interactions explored, the data used, and their main findings.

Chapter 2

This chapter elaborates on the learning analytics perspective adopted in this dissertation, interactions in educational contexts, digital ecosystems and educational resources, and the temporal element of learning. It provides a theoretical background for the other chapters in the dissertation.

Chapter 3

In this chapter, an overview of the methodological approach adopted in the dissertation is presented. Moreover, it outlines ethical considerations pertinent to the analyses included in the following chapters. The chapter concludes with a declaration of authorship in adherence to Reykjavik University rules.

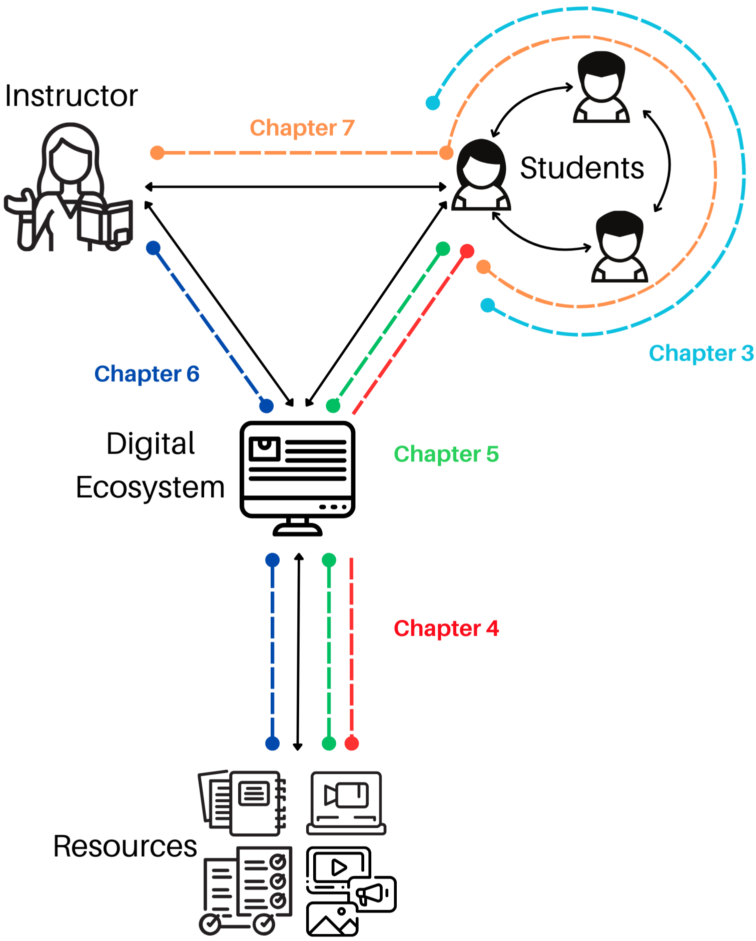


Figure 1.2: Overview of the chapters in the dissertation.

Chapter 4

In this chapter, we explore student ↔ student interactions. We present a social network study of students' social connections for identifying study profiles in higher education. The data for this study were gathered through an online survey distributed to undergraduate students in 2019.

- We build a student social network based on a survey where the students shared their perspectives and preferences in regard to their undergraduate studies and listed their closest social connections at the university.

- We identify student communities by implementing a community detection algorithm.

- We characterise the study profiles of the communities identified based on the students' survey answers regarding learning preferences.

- Our study provides an overview of five learning profiles and the characteristics that distinguish them, and how they might evolve as the students progress.

- According to the study profiles identified, we show that not all the students were impacted in the same way when the pandemic forced the shift to online environments.

This chapter has been published in

N. López Flores, A. S. Islind, and M. Óskarsdóttir, "Exploring study profiles of computer science students with social network analysis," in *The 55th Hawaii International Conference on System Sciences (HICSS)*, ser. The 55th Hawaii International Conference on System Sciences (HICSS), Jan. 2022. DOI: 10.24251/HICSS.2022.214

Chapter 5

In this chapter, we examine student ↔ content interactions. We present a quantitative analysis of the use of educational material by high and non high achievers in order to provide insights on the differences in the use of educational materials in both groups. The data used for this study was gathered through two digital platforms.

- We explore the differences in the use of lecture recordings and slides by high and non high achievers.

- We analyse the differences in how these groups access and interact with the resources provided before, during, and after solving and submitting assignments.

- We found a positive relationship between the time high achievers spent solving assignments and the usage of slides and lecture recordings.

- In contrast, non high achievers had lower engagement levels with the resources and digital platforms.

- The results highlight the value of considering all the digital educational platforms to evaluate the evolution of students' learning strategies.

This chapter has been published in

N. G. López Flores, A. S. Islind, and M. Óskarsdóttir, "Making the most of slides and lecture captures for better performance: A learning analytics case study in higher education," in *The 56th Hawaii International Conference on System Sciences (HICSS)*, Jan. 2023, pp. 1291–1300. DOI: 10.24251/HICSS.2023.159

Chapter 6

This chapter explores both student ↔ digital ecosystem and student ↔ content. The data used for this study was gathered through two digital educational platforms, and semi-structured interviews with students.

- We present a three step action LA research case including three phases (exploration, intervention, and evaluation).
- We investigate student ↔ system interactions before, during, and after the COVID-19 pandemic.
- We examine changes in student ↔ learning resources interactions under different teaching modalities and class schedules.
- Our analyses show that students modified their time organisation habits during the pandemic. The intervention had no effect on the grades distribution.
- We show that digital ecosystem, and learning resources interaction data are insightful elements for driving schedule interventions.

This chapter has been published in

N. López Flores, A. S. Islind, and M. Óskarsdóttir, "Digitalization and digital competence in educational contexts," in Routledge, Dec. 2023, ch. A learning analytics-driven intervention to support students' learning activity and experiences, pp. 81–102, ISBN: 978-1-00-335569-4. DOI: 10.4324/9781003355694-10

Chapter 7

In this chapter, we explore instructor ↔ digital ecosystem/content interactions. It presents the creation and adoption of a university-wide programme for supporting instructors in creating and providing educational resources. The data in this study was gathered through semi-structured interviews.

- We adopt a socio-technical perspective for evaluating potential uses of a digital educational platform during and after the pandemic.
- The study encompasses the analysis of social (instructors) and technical (digital platform) subsystems to inform the programme design and support resources provision.
- The programme supported instructors by providing guidelines, tutorials, and advice for organising resources within the digital platform, improving consistency and allowing for easier student interaction and resource retrieval.
- The programme aimed to improve the learning experience for students after the pandemic by ensuring consistency across the digital platforms used for teaching.
- The programme facilitated data collection, improving both the quantity and quality of data for LA research.

This chapter has been submitted for publication in

N. G. López Flores, M. Óskarsdóttir, and A. S. Islind, "Supporting teachers in higher education: Design of an institutional programme from a socio-technical perspective," *Frontiers in Education*, (Year), in submission

Chapter 8

This chapter presents a summary of two studies addressing student ↔ student and student ↔ instructor interactions. The data for these studies were gathered from an online discussion forum platform used in undergraduate courses.

- We use network analysis to explore student ↔ student interactions as well as student ↔ instructor interactions under different teaching modalities and how they changed during and after the pandemic.
- We evaluate the extent to which temporal variables created based on the social network structure inform the identification of students at risk.

- Our analyses show how the change in teaching modality not only impacted activity levels, but also the way interactions took place.
- The results provide insights on the role the instructors played and the workload increase they experienced during the pandemic.
- We found that interaction dynamics in discussion forums have low predictive power due to the complexity of the data and the sparsity of the observations.

The first study has been published in

N. López Flores, M. Óskarsdóttir, and A. S. Islind, "Analysis of discussion forum interactions for different teaching modalities based on temporal social networks," in *Proceedings of the NetSciLA22 workshop, March 22, 2022*, 2022, pp. 23–32. [Online]. Available: https://ceur-ws.org/Vol-3258/article_3.pdf

The second study has been submitted for publication in

N. G. López Flores, V. Uc Cetina, A. S. Islind, *et al.*, "Threads of complexity: Lessons learnt from predicting student failure through discussion forums' social-temporal dynamics," in *Frontiers in Education FIE 2024*, under review, 2024

Chapter 9

This chapter discusses the significance of the findings in previous chapters for LA research and how they address challenges and limitations. Furthermore, it thoroughly examines how the findings of the dissertation compare and support LA research on interactions, outlining a conceptual framework for LA research on learning strategies from an interaction perspective. In this chapter, practical implications of the dissertation concerning data, resources, and support are presented and contextualised. Finally the chapter concludes with a discussion on the research limitations, potential biases and constraints of the dissertation as a whole.

Chapter 10

The final chapter concludes the dissertation by presenting closing thoughts and the key learning points and contributions. Additionally, it looks ahead, presenting future research directions and identifying new questions and challenges that emerged from this dissertation.

Chapter 2

Related work

The previous chapter discussed briefly the LA field and presented the research focus of this dissertation. This chapter provides a more detailed introduction to relevant elements, including the learning analytics perspective adopted throughout the dissertation, the investigation of interactions in educational context, digital ecosystems and educational resources, and the temporal element of learning.

2.1 Learning analytics perspective

Learning is a multidimensional process that evolves and changes, influenced and affected by several elements. Consequently, to gain a deeper understanding of learning processes,it is beneficial to analyse educational data through a comprehensive approach focusing on key factors and how they influence each other. As presented in the previous chapter, this dissertation investigates interactions in educational contexts. The importance of interactions in higher education has been widely acknowledged and investigated by adopting various perspectives and learning theories, each of them emphasising on a particular type of interaction. For instance, the social learning theory [52] highlights the importance of learning within social contexts, where individuals have the opportunity to learn and develop new skills and behaviours by observing and engaging with others in their social circles. The self-regulation theory views learning as a dynamic process that unfolds through a continuous cycle involving four stages: task definition, setting goals and planning, implementing learning strategies, and evaluating and adjusting performance [53]. Connectivism on the other hand is a digital learning theory that describes learning as the process of connecting objects, artifacts, and individuals into a distributed network [54], underscoring the significance of connectedness and interactivity, particularly in relation to the connections between people and those between people and technology [55]. Finally, socio-technical perspectives underscore the interactions between individuals and the technology utilised to facilitate learning and performance, emphasising the role that both social and technical subsystems play in establishing efficient learning settings [56], [57]. These theories and perspectives, which will be discussed in more detail in the following subsection, have proven to be highly valuable for educational research.

LA emphasises a wide range of analytical approaches aimed at understanding and improving learning processes[58]. A systematic review conducted by Dutt, Ismail, and Herawan [59] highlights the use of both hierarchical and non-hierarchical clustering algorithms in educational data mining, emphasising their potential to inform student performance, understanding learning preferences, and advance student modelling. Leitner, Khalil, and Ebner [40] and De Witte and Chénier [60] emphasise the importance of understanding interactions within learning environments through social network analysis, text mining, and temporal analytics. They also advocate for the use of process mining and natural language processing to analyse synchronous and asynchronous communications. In addition, reviews conducted by Roy and Singh [61] and Aldowah, Al-Samarraie, and Fauzy [62], mention the utilisation of various methodologies, including classification, regression, pattern mining, visual analytics, and recommendation systems. Furthermore, Aldowah, Al-Samarraie, and Fauzy [62] underscored the comprehensive nature of these methodologies in four dimensions, including computer supported learning, predictive, behavioural, and visualisation analytics; and their value to derive actionable information based on students interaction and identify activity patterns. Lemos dos Santos, Cechinel, Nunes, *et al.* [63] systematic review highlighted the prevalence of statistical methods, machine learning, social network analysis, and information visualisation for LA research in Latin America. The authors also reported on an open survey distributed to 28 research groups. In contrast to the methods found in the systematic review, the survey results indicated data mining, educational research methods, and statistical analytics were the most commonly used, whereas semantic web, text mining, and social network visualisations were the least explored methods. Pinto, Abreu, Costa, *et al.* [64] review focused on machine and deep learning methods applied in higher education, finding neural networks and supervised techniques such as random forest, support vector machines, and regression to be the most widely used. Finally, Hoppe [65] contributed to this discussion by examining computational and algorithmic methods used to analyse learning interactions; introducing three main methodological approaches, content-oriented, process oriented, and network analysis, each of them representing a unique perspective in educational data analysis. Firstly, content-oriented analysis focuses on examining learner-created artefacts to identify patterns within the content, and provide insights on learning interactions, the dynamics of learning and knowledge building. Process oriented methods involve the exploration of temporal sequences of events and interactions such as action logs to shed light on their patterns, and their change over time. Finally, network analysis encompasses social and actor-artefact interactions. It involves studying the relationships and interactions between actors, and methods for quantifying their importance, to provide insights into patterns and the overall structure of the network.

Collectively, these studies demonstrate a growing trend towards the use of complex computational methods to analyse and interpret educational data. Nonetheless, qualitative methods also form a part of the methodological approaches adopted in LA research, including interviews, observations, focus groups, content analysis, and case studies. These methods are often used to conduct mixed-methods research by combining them with quantitative approaches (see e.g. [44], [66]–[69]). These qualitative methods can be valuable for analysing contextual data and provide deeper insights into learning processes and behaviours.

Throughout this dissertation, the analytical approach adopted for the investigation of interactions in higher educational contexts is mostly quantitative, relying on statistical methods and network analyses. Furthermore, qualitative methods including semi-structured interviews with students and instructors on their perspectives and usage of the system and resources were also used to inform the implementation and effect of interventions.

2.2 Interactions in educational contexts

The notion of interaction, generally defined as “an occasion when two or more people or things communicate with or react to each other” [70] has been extensively explored across multiple domains [71], including education where they have been found to be crucial for effective learning [72].

In the context of education, interactions can be described as the various ways of communication and engagement that occur between learners, instructors, learning material, and technology in the learning process [72], [73]. By delving into the interactions that take place in higher education, valuable insights can be obtained to deepen our comprehension of student learning patterns and behaviours. Such understanding is crucial not only for refining educational methods and enhancing the overall learning experience, but it is also essential to build and adapt theories of interaction on [72].

Core interactions in educational settings are usually of three types: learner-content, learner-instructor and learner-learner, as defined by Moore [74] in relation to interactions in distance education in the early 1990s. Anderson and Garrison [75] emphasised on six possible ways of interactions that emerged from the model of transactional relationships proposed by Garrison [76] (Figure 2.1) and the role they play to uphold learning. In addition to the three interactions proposed by Moore [74], Anderson and Garrison [75] also stressed on the importance of learner-learner, instructor-instructor, and content-content interactions. At the intersections between the three macro-components in Garrison's model [76] (student, instructor, and content) are the dimensions support, independence, and proficiency. Independence, the intersection between instructor and content, refers to the students' freedom to "choose and pursue educational goals" [76, p.27]. Support, the intersection between student and instructor, refers to the "range of human and nonhuman resources to guide and facilitate educational transaction" [76, p.29]. Proficiency, the intersection between student and content, is understood as the "students' ability to learn independently" [76, p.29]. Meaningful learning can be found at the intersection of these three dimensions when the three dimensions are in dynamic balance [75]. As with the increased access to communication technologies and the availability of distance learning programmes, the investigation of interactions and their role in facilitating effective and meaningful learning also expanded, including interactions student-interface, group-content, group-group, learner-group, and instructor-group [72] [1].

Connectivism is a digital learning theory, that highlights the importance of networks and interactions for learning [54]. Connectivism, as envisioned by Siemens, pays special attention to the role of technology and its impact on learning, contrarily to other learning theories that were developed and adopted before [54]. Although connectivism recognises the agency of the learner for knowledge creation [77], the theory further holds that the learning process is not entirely under the learners' control, with new tools influencing the way learners work and function [54]. Furthermore, connectivism considers that learning is not an individualistic practice as it does not occur isolated from the social context [77]; rather social connections play a significant role for the occurrence of effective learning [54], [78]. In connectivism, learning is understood in the context of ever-changing social environments in which it occurs, emphasising on the importance of adapting to the dynamic nature of society and chaotic environments [54], [77].

The role of interactions in connectivism is essential, as learning is seen as the process of "connecting specialised nodes or information sources" [54, p.7]. Furthermore, connectivism is a model of knowledge acquisition, where knowledge is the result of interactivity with both human and non-human appliances [54], [77]. Consequently, development and adoption of connectivist approaches in

[1] In this dissertation, interactions will be defined for students, instructors, digital ecosystem, and content. The inclusion of other terms such as learner, teacher, or interface corresponds to previous literature and will be maintained as per the original authors' presentation.

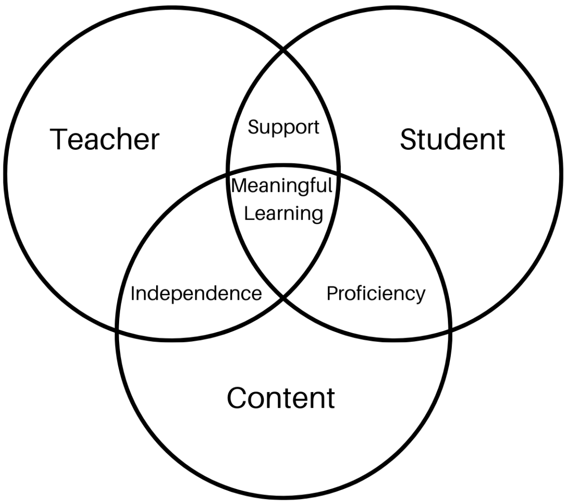


Figure 2.1: Model of transactional relationships in higher education [76].

the future of learning and development is underscored by the hype and spread of digital learning environments [77]. Based on the connectivist learning theory principles [54], and Anderson and Garrison [75] transactional model, two types of interactions can be recognised in educational environments, human-human and human-system interactions.

Human-human interactions

In educational contexts, human-human interactions relate to the social element of learning, including student-student, student-instructor, and instructor-instructor interactions. These interactions support learners' knowledge and learning acquisition, and are essential for learning processes, because learning is not an individual achievement, but rather a socially-regulated process that thrives on communication and collaboration [79]. These statements are widely supported by the social learning theory, which establishes that learning happens in social environments, and the students learn from social interactions in communities and groups [52]. The investigation of social interactions is also an essential part of LA research. Social Learning Analytics (SLA), a sub-field of LA, aims to integrate the social perspective into LA research to better understand learning processes, in contrast to other individualistic approaches that focus only on students' personal characteristics and behaviour to analyse and describe learning patterns and strategies [80]. Ferguson and Shum [81] defined SLA as "a distinctive subset of learning analytics that draws on the substantial body of work demonstrating that new skills and ideas are not solely individual achievements, but are developed, carried forward, and passed on through interaction and collaboration".

Social Network Analysis (SNA) is the methodological approach most frequently used to investigate the social component of learning [80], [82]. The investigation of social interactions in educational settings, has led to significant findings about learning processes. Applications of SNA in higher education have addressed multiple topics, including the analysis of network dynamics of Massive Open Online Courses (MOOCs) and discussion forums to predict activity levels and connections creation and evolution [61], [83]–[86], academic success and dropout [83], [87], the influence of group creation and homophily on learning and academic performance [88]–[90], content analytics [91], study patterns [92], and collaborative learning [93].

The findings and advances in educational research based on networks have also helped to find out the current challenges and limitations for further research in the field. Saqr, Poquet, and López-Pernas [94] summarise network-related research in education over five decades, from 1969 to 2020. Their research highlighted an increasing interest in understanding interactions, metrics, temporality, and their relationship with academic achievement. Poquet and Joksimović [95] provided a detailed review of network-based empirical research on educational settings. The authors' analysis emphasises the need for more rigorous operationalisation of networks, interpretation of network centralities, and network models. Their work also identified future areas of development in the field of SLA: temporal, multiplex, and dynamic network modelling. In a recent literature review, Kaliisa, Rienties, Mørch, *et al.* [80] also reported on the future directions and needs in the field, emphasising methodological and implementation challenges. Among them, the need for heterogeneous data sources, temporal analysis, the inclusion of varied educational settings, and the need for institutional applications are mentioned. In general, as it has been presented, the study of the temporality of networks in education is still in its early stage. Furthermore, the low percentage of scientific publications that focus on analysing the evolution over time of networks created based on educational data has been highlighted [94].

Human-system interactions

[2] Human-system interactions on the other hand include both student-system/content, and instructor-system/content interactions. The investigation of these types

[2] The main body of this section also appears in Sections 5.2.1 and 7.2.2.

of interactions is intricately linked to digital ecosystems, due to their role in resource provision and data collection, storage, and analysis.

Digital ecosystems capture and store the students' detailed activity within the system elements and modules; as well as the students' interactions with the learning materials provided by the instructors. In consequence, large data sets of time stamped clickstreams -or digital traces- are produced, providing insights into educational practice [32]. The massive amounts of educational data and digital traces from LMSs and interactive learning environments are a common source of data in LA research and have been widely used with the objective of investigating several elements of learning and teaching processes [96], [97]. Previous research based on these data has highlighted digital learning platforms' data are a helpful resource that allows to investigate the students' engagement, self-regulation, and time management skills [98]–[100].

Self-regulated learning has been defined as a process that involves four recursive stages: (i) task definition, (ii) goal setting and planning, (iii) enacting study tactics and strategies, and (iv) adaptation [53]. This model of self-regulated learning defined by Winne and Hadwin [53] has been extensively adopted in computer supported learning environments [101]. In this model, given a learning task; (i) and (ii), involve the students' task understanding, and their plan for addressing it, respectively. In (iii), the study tactics and strategies selected based on (i) and created in (ii) are implemented, whereas in (iv) the students change their learning strategies based on the experience and evaluation elements. Several indicators based on digital learning platforms clickstreams have been created to analyse self-regulation behaviours, build dashboards, and inform both learners and instructors [102]. Some examples of those indicators are the students' level of engagement, time utilisation, posting activity, etc.

The existing research on digital platforms and ecosystems, often puts weight on the technical aspects of these systems without considering their social context, which is essential for understanding platform dynamics [103]. In contrast, research undertaken from a socio-technical perspective accounts for the interactions between two components or subsystems, without utilising either the social element or the technical element as the focal point. These interactions have been conceptualised in a socio-technical system defined as the "Recognition of a recursive (not simultaneous) shaping of abstract social constructs and a technical infrastructure that includes technology's materiality and people's localised responses to it" [56, p.42]. Although the definition of socio-technical systems has evolved, the underlying concept remains the same, recognising the importance of both the technical and the social subsystems [57]. The technical subsystem includes the physical infrastructure (hardware), software, and the associated platform mechanisms [57]. The social subsystem, on the other hand, is composed of individuals, relationships, and human attributes [57]. An integrated socio-technical perspective attempts to understand subsystem interactions, optimise their fit or harmony, and improve platform (instrumental) or social (humanistic) outcomes [57].

Bednar and Welch [104] emphasise the socio-technical nature of learning. They describe learning as efforts to leverage internal and external procedures, and note its evolutionary characteristics. Nonetheless, although the socio-technical perspective emphasises the importance of interactions between the subsystems, the whole system can be characterised by four elements, namely, people (or actors), technology, task (or process), and structure (or communication tools or resources) [105]–[107]. In educational contexts, these elements correspond to instructors and students, the digital platforms used for teaching, the knowledge or skills being communicated, and the environment, respectively [108]. These elements and their characteristics, including users' backgrounds, technology fit to the task requirement, as well as task and system attributes, influence the adoption of digital educational platforms, including learning management systems and their integrated elements [106].

2.3 Digital ecosystems and educational resources

Digital technology-based learning environments such as digital ecosystems and educational platforms play a vital role for providing and accessing educational material, and facilitating communication among students and instructors [14], [51], [109]. Digital ecosystems, also called educational or learning platforms, can combine several components including learning management systems, student management systems, embedded tools, and external digital platforms. The digital traces produced and stored by digital ecosystems empower educational researchers from varied interrelated fields (e.g. learning analytics, educational data mining, and educational data science), to investigate several factors of teaching practices and learning processes. Nevertheless, instructional conditions such as course design, the digital technology used, and the implemented teaching modality as part of the courses' instruction, should be taken into account for LA research [42].

Learning management systems (LMSs) are among the principal components of digital ecosystems. LMSs are internet-based software platforms designed to facilitate and organise course content, student learning activities, and assessment in formal learning environments [110], [111]. The adoption of LMSs among universities widely spread since the late 90's with the accelerated internet and multimedia advancements [112]. Multiple LMSs have been released and adopted by higher education institutions. Most of them share common characteristics for facilitating and enhancing teaching practices, and features for stimulating and improving students' learning [110], [112]. These systems enable seamless creation and delivery of course content, granting learners on-demand access to educational resources. Additionally, they support synchronous and asynchronous communication, upholding interactions among students and instructors. Furthermore, they enhance the students' learning experience by allowing the integration of external tools and multimedia resources, facilitating collaborative work, and providing time management tools, such as calendars, to-do lists, and reminders. Ultimately, LMSs also offer valuable features for instructors, including the capability of streamline the grading process with tools for automated grading and feedback provision, and analytic tools for monitoring students' engagement and academic performance [36], [107], [112]. LMSs can also be linked to other systems or digital platforms within the same institution [112], such as digital platforms for streaming, conferencing, lecture recording, coding, and communicating with other participants. Figure 2.2 shows an example of a digital ecosystem with its elements integrated.

The educational resources provided to the students are also an essential component of digital ecosystems. Their importance was emphasised during the COVID-19 pandemic, as they played a key role in ensuring continuity in education. Considering lecture recordings and online discussion forums were crucial for facilitating education delivery and communication, in the following an emphasis is placed on these educational resources.

Lecture recordings

Lecture recordings have been told to be a valuable resource for students in higher education, providing flexibility, enhancing accessibility, and supporting deeper learning [113]. Previous research on lecture recordings has mainly focused on two aspects, users' perception of lecture recordings provision, and the usage made of those recordings and its relationship with academic performance. Investigating the students' and teachers' perception has been addressed using varied approaches. Morris, Swinnerton, and Coop [114] analyse data from LMS and surveys distributed to students and teachers to investigate their perceptions on the effect of lecture recordings over teaching and learning processes. Their research showed the lecture recordings were a valuable resource for students, as their provision helped them to keep on track of their studies, submit assignments, and revise materials after class and before assessments. On the other hand, instructors had several concerns about the effects of lecture captures on the students' engagement and attendance levels. Moreover, the instructors reported the lecture recordings modified their teaching style, having also a negative effect on the students' note-taking and time management skills. Nkomo, Ndukwe, and Daniel [115] applied network science and sentiment analysis approaches to investigate the students' perspectives on the value of lecture recordings. Their findings showed that the students did not see lecture recordings as a replacement for live lectures, but as a complementary

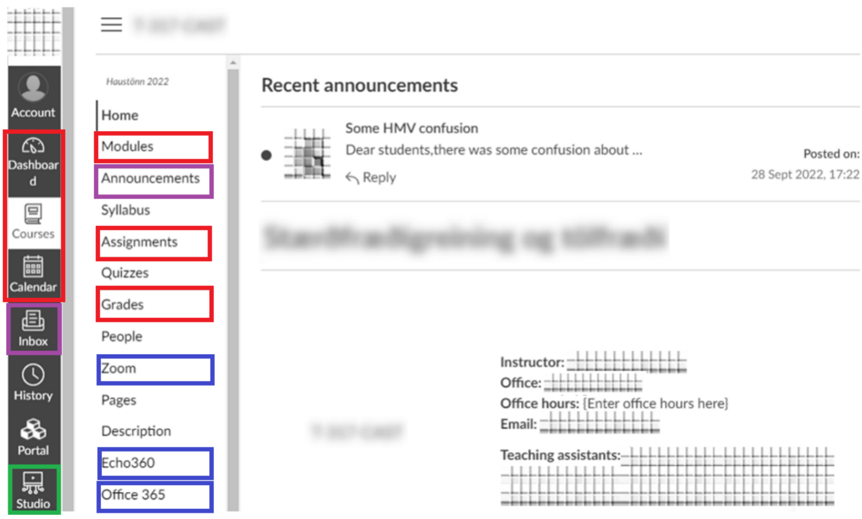


Figure 2.2: Digital ecosystem example; features for students access to courses' content and management (red), communication features (purple), resources creation features (green) and external digital platforms (blue). There might be an overlap between these categories; for example, Echo360 is at the same time an external digital platform and a creation feature.

learning resource for assignment submission and further study. The authors also identified the need for the development of institutional policies to manage downloading and sharing rights.

Regarding the usage of lecture recordings, the most common data source is the log data from LMS and external digital platforms. Nordmann, Calder, Bishop, *et al.* [113] focused their research on analysing the relationship between lecture recordings' usage, attendance, and academic performance. Their research showed that using lecture recordings as replacement for lecture attendance had a negative impact over the students' academic performance. On the contrary, lecture recordings used as complement learning materials had a positive impact on the final grade. Their research also highlighted the effect of maturity and year of study, as younger students from earlier years benefited the most from lecture attendance. Their work identified further areas of lecture recordings research, including longitudinal and temporal analysis for identifying differences between students from different years, and gain a better understanding of when the students watch the lecture captures. Sarsfield and Conway [116] used server log data to examine changes in lecture recording usage over time, as well as differences between subjects, subgroups of students, and recording types. Their research showed that students from different majors watched lecture captures in a different way, as well as a correlation between access time and the final grade obtained. Moreover, the authors identified the need to study how high-performing students use lecture recordings, investigate differences between majors and subjects, and integrate qualitative research methods. The lecture capture usage patterns of students from different academic years have revealed that student behaviour relies on many factors such as the courses and cohorts in which they are enrolled [117].

Online discussion forums

Online discussion forums, sometimes referred to as asynchronous online discussions [118], allow students to take part in class-related discussions at any time and in any physical location. The analysis of discussion forum data has been performed over different educational contexts and teaching modalities. Yang, Tang, Hao, *et al.* [119] investigated the relationship between content related contributions and academic performance in Massive Open Online Courses (MOOCs). In their studies, decision trees and longitudinal k-means methodologies were used to classify posts and to cluster students into five categories according to their temporal posting behaviour. Their research confirmed longitudinal forum participation as a predictor of academic performance. Interactions occurring through online discussion forums have been helpful in investigating social interactions in educational contexts. For instance, Lee, Rothstein, Dunford, *et al.* [118] used SNA to study asynchronous online discussions in blended environments. In their research, by combining multiple linear regression with outlier analysis, patterns of engagement for help-seeking and help-providing were identified, as well as the relationship between these patterns and academic performance. Their results do not show evidence of a direct relationship between academic performance and posting frequency. Similarly, Saqr and López-Pernas [120] analysed data from online collaboration tasks of 69 courses. In their work, centrality measures such as degree and eigenvector centrality were found to be consistent indicators of academic performance. In a comparable study, Williams-Dobosz, Azevedo, Jeng, *et al.* [84] analysed centrality measures for help-seeking and influence based on online discussion forum and its relation with academic performance and course improvement for students traditionally underrepresented in STEM. In their research, whereas centrality measures related to help-seeking were significantly related to improvement, centrality measures related to connectivity did not have a significant effect.

2.4 Temporal element of learning

Learning, like many other real phenomena, is a dynamic process that occurs over time [121], [122]. Time is a noteworthy dimension for educational research, as it plays a crucial role in shaping the learning process. Understanding the effect of time on learning processes is essential for LA research, as it enables us to gain insights to better understand and optimise learning [122]–[124]. Temporal analysis is useful for identifying and describing learning mechanisms, their variations, and the transitions among them [125]. Molenaar and Wise [125] presented a framework for the concepts of time to support temporal analysis. The authors introduce the concepts passage of time and order in time. The former focuses on four metrics of the time flow related to a specific learning event: position, duration, frequency, and rate. In contrast, the latter focuses on relationships, transitions, and organisation among learning events, including consistency, regular recurrent changes, non-recurrent regular changes, and irregular changes between events.

Furthermore, the impact of time on learning processes is a fundamental aspect for investigating self-regulation behaviours, communication dynamics, and academic performance. Saqr, Nouri, and Fors [123] analysed temporal indicators of student activity to identify differences in daily, weekly, course, and academic year activity between high and low achievers. Their research showed that activity levels during working hours and early activity during the week and course are reasonable predictors of high and low performance at early stages, in contrast to approaches that consider accumulated activity demonstrating the temporal component is correlated with academic performance. In a comparable study, Saqr, Nouri, and Fors [124] investigated the self-regulated temporal patterns in online environments. By analysing the students' communication events with their course peers, the researchers showed the activity levels decreased along the year, and the temporal variables as indicators of self-regulation have the potential to enhance our understanding of learning processes.

Despite the promising results obtained recently in the field of LA and the increasing interest in temporality, it has been highlighted that this dimension of learning processes and its effects are still underexplored [94], [126]. More research based on independent and integrated approaches, focusing on the temporal element of learning is needed to address methodological, conceptual, and pragmatic challenges [126].

Chapter 3

Methods overview

This chapter briefly describes the methodological approach utilised in the dissertation, offering an overview of the various data sources and analysis methods employed in the following chapters.

The approach adopted is characterised by a six-stage process structured based on the elements of the LA cycle: learning environment, big data, analytics, and act [36]. The process, displayed in Figure 3.1, comprises the steps problem definition, data collection, exploratory analysis, analysis, interpretation, and recommendations.

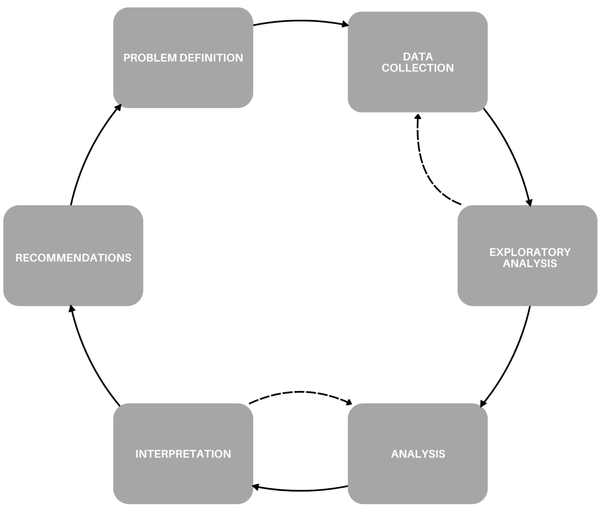


Figure 3.1: Overview of the research analysis process.

The first step is problem definition. This step includes a review of the literature related to the topic of interest to identify research gaps and limitations raised by previous studies. Similarly, it includes questions produced by particular circumstances identified and experienced at the higher education institution where this research takes place. In this step, the initial research question(s) for each paper are defined.

Following the establishment of the problem, the second step is data collection. It involves the gathering of relevant data for informing the study. In this dissertation, data were collected from varied sources. Quantitative data from the digital ecosystem components were accessed through the digital platforms' Application Programming Interfaces (APIs) and activity reports downloaded from the digital platform. Qualitative data were gathered through surveys and transcripts of semi-structured interviews. Table 3.1 lists the data sources included in each of the papers presented.

Table 3.1: Data sources included in each chapter in the dissertation.

Chapter	Data sources
Exploring Study Profiles of Computer Science Students with Social Network Analysis	(1) Survey (2) Closest connections self-report.
Making the Most of Slides and Lecture Captures for Better Performance: A Learning Analytics Case Study in Higher Education	(1) LMS: activity reports (2) LMS: grades report (3) Lecture recording activity
A Learning Analytics Driven Intervention to Support Students' Learning Activity and Experiences	(1) LMS: activity reports (2) LMS: Grades report (3) Lecture recording activity (4) Semi-structured interview transcripts
Supporting Teachers in Higher Education: Design of an Institutional Programme from a Socio-technical Perspective	(1) LMS: courses list (2) Semi-structured interview transcrips
Socio-temporal insights on online discussion forum interactions	(1) LMS: grades report (2) Discussion forum activity

After data collection, an exploratory analysis of the data is conducted. This step involves preliminary data examination to identify initial trends and patterns, as well as anomalies in the case of qualitative data. Figure 3.1 indicates an iterative process of exploratory analysis and data collection when initial findings led to the collection of additional data.

Following the exploratory analysis step, the process moves towards deeper analysis. Qualitative and quantitative analyses were performed in this step. Firstly, for quantitative analyses, it included data source merging and feature engineering. Merging activity reports from different digital platforms is complex. To merge the reports correctly, each report was carefully analysed to grasp the meaning of each variable. Feature engineering is the process of creating variables that act as representations of data, which are helpful for analysing processes inherent to the nature of the phenomena observed [127]. In this context, examples of such processes include engagement, self-regulated learning, and time management skills. Several variables were created depending on the analyses needs. Quantitative analysis included statistical analyses, network methods such as community detection, as well as machine learning algorithms. Qualitative data was analysed through content analysis of semi-structured interviews with students and professors. Detailed information regarding the analyses undertaken is provided in the methods section included in each chapter.

The next step was interpretation. In this step, the analyses' results obtained from the previous step were translated into meaningful findings about the educational context investigated to provide an answer to the research question, contributing to the understanding of the defined problem. In some cases, the results and interpretation led to further inquiries, which were investigated through a recursive cycle between the steps analysis and interpretation.

Finally, recommendations are derived from the interpreted data, informing suggestions based on the research findings. Considering that these recommendations would potentially motivate subsequent studies and the development of new research questions to be solved, the cycle closes back towards problem definition.

3.1 Ethical considerations

Students enrolling in Reykjavik University's academic programmes are informed that their data could be used for research aiming at improving teaching and learning practices, and informed consent is required. In addition, after reviewing the research objectives, the Legal Council and Teaching Affairs Offices at Reykjavik University granted written authorisation for data collection and analysis.

All qualitative and quantitative data used throughout the development of this dissertation were stored in a restricted access drive hosted by the Information Technology Department at Reykjavik University. The drive was password protected, and accessible only by the researchers involved, adhering to the institution's policies.

Quantitative data was extracted from the LMS, Echo360, and Piazza. The activity reports downloaded from the LMS and included in the analyses did not include identifiable information. The system automatically assigns a numerical identifier that does not include personal information (e.g. social security number). These identifiers can be accessed through the systems' API and were not stored. The merging process across digital platforms was done through the students' institutional email. After merging, the data went through a pseudonymisation process, by removing the email and replacing it with a numerical identifier. Furthermore, in cases where the study required collaboration with researchers from different affiliations, the pseudoanonymised data was made available to them after the information had been randomly shuffled.

Participants part taking in surveys and semi-structured interviews was voluntary. The semi-structured interviews were conducted both online and face-to-face, participants were informed about the research objectives and asked for their authorisation for audio recording. Audio files were transcribed verbatim and will be deleted after the conclusion of this Ph.D. research. The information disclosed in semi-structured interviews was anonymised after transcription by removing personal identifiers.

3.2 Researcher's role

Following Reykjavik University's rules, a declaration of authorship contribution must be submitted to the RGCS in the Computer Science Department. The declaration reports my degree of involvement at different stages of research and publication process of the papers included in this dissertation. Following the rules described in Appendix A, Table 3.2 presents my authorship contribution to the six papers included.

Table 3.2: Declaration of authorship contribution.

Paper name	Idea	Related work and literature	Data gathering	Research Design	Artifact Design	Analysis and synthesis	Draft	Administration
Exploring study profiles of Computer Science students with Social Network Analysis	EE	ME	LE	LE	EE	ME	ME	ME
Making the Most of Slides and Lecture Captures for Better Performance: A Learning Analytics Case Study in Higher Education	ME	ME	ME	EE	ME	ME	ME	ME
A Learning Analytics Driven Intervention to Support Students' Learning Activity and Experiences	EE	ME	ME	EE	EE	ME	ME	ME
Supporting teachers in higher education: Design of an institutional programme from a socio-technical perspective	EE	EE	ME	EE	EE	ME	ME	ME
Analysis of discussion forum interactions for different teaching modalities based on temporal social network	EE	ME	ME	ME	EE	ME	ME	ME
Threads of complexity: Lessons learnt from predicting student failure through discussion forums' social-temporal dynamic	ME	ME	ME	ME	EE	ME	ME	ME

Chapter 4

Exploring Study Profiles of Computer Science Students with Social Network Analysis

Digital technology[1] is widely adapted in all levels of education. The extensive information resources facilitate enhanced human capacity and the social environment to support learning. In particular, Social Network Analysis (SNA) has been broadly used in teaching and learning practices. In this paper, we perform community detection analysis to identify the learning behaviour profiles of undergraduate computer science students in a Nordic university. The social network was created using 273 responses to an online survey. The students themselves provided their social connections at the university, and node attributes were created based on responses to questions regarding educational values, goals orientation, self-efficacy, and the university teaching methods. We analyse the biggest communities to identify the factors that characterise the learning strategy and preferences of undergraduate computer science students.

4.1 Introduction

Digital technology[1] has become an essential tool of education. It is rich in information resources and can extend human capacity and the social environment to support learning. As part of its rapid growth, Social Network Analysis (SNA) has been broadly used in teaching and learning practices [128]. Recent literature suggests that the potential of Learning Analytics and Educational Data Mining offer benefits through the use of educational data both for teachers

[1] Referred to as ‘Information technology’ in the published manuscript [1].

and students to further understand the way students approach their learning [96]. With the increase in online learning brought on by the COVID-19 pandemic, there is a greater need for understanding students' social structures in relation to study preferences and motivation so that universities can better accommodate the needs of more students, especially of underrepresented students [129].

This paper analyses and describes the study profile of undergraduate students of four Computer Science related programmes through Social Network Analysis and community detection. In particular, we are interested in knowing their learning preferences regarding group working, physical attendance of lectures, self-efficacy perception and goal orientation. We aim to answer the research question: *Can Community Detection algorithms applied to the social network of students identify undergraduate study profiles at a Computer Science Department?* To answer the question, we analysed the social connections of undergraduate students and their study preferences to outline their study profiles. The social network is built based on an online survey created and distributed in 2019 to 717 undergraduate computer science students to investigate their learning patterns and behaviours. The students' social network is assortative and has a high clustering, common features in social networks. We discover five communities of students, where each of them is characterised by a different study profile.

The rest of this paper is organised as follows. In the next section, we discuss related research on learning analytics, educational data mining, SNA and study profiles. In Section 4.3 we present the methodology used in this research followed by the results in Section 4.4. The paper concludes with a discussion on the implications and limitations of our work and directions for future work.

4.2 Related work

4.2.1 Learning analytics and educational data mining

Learning Analytics (LA) and Educational Data Mining (EDM) have emerged as impactful research fields that draw on educational data in the last decades [32]. LA is defined as the "measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimising learning and the environments in which it occurs" [32]. The implementation of LA strategies has been highlighted among the priorities of higher education institutions [130]. However, EDM is defined as "an emerging discipline, concerned with developing methods for exploring the unique types of data that come from educational settings, and using those methods to better understand students, and the settings which they learn in" [59], it employs data mining theories and techniques to analyse educational data. Both LA and EDM aim to improve and create methods that enhance education at all levels. They revolve around personalisation, adaptive learning, predictive analysis and user behaviour profiling [131], [132]. Furthermore, LA and EDM methods have been widely applied to address a large set of concerns, e.g., predicting students' performance, retention analytics, intelligent feedback provision and course recommendation [61]. Notwithstanding, limited research on learning styles like the personalisation of learning, learning style identification and its application in teaching, learner motivation, and student profiling has been carried out [59].

Among the data mining techniques used in EDM, prediction methods, like classification and regression, and structure discovery methods, like clustering and factor analysis, are the most commonly used. Most recent research in EDM had been focused on the use of two or more methods [133]. Usual clustering and classification problems in EDM and LA can be extended to Social Network Analysis [134], [135]. However, Social Network Analysis has been used less frequently to examine educational data [133].

4.2.2 Network science in educational context

Among SNA applications in the educational context, recent research has been focused on a wide range of areas of interest. Homophily is a fundamental property of social networks; it establishes that people with similar properties are more likely to connect [136]. Nguyen, Poquet, Brooks, *et al.* [89] analysed homophily regarding gender, ethnic minority identity, family income, and academic performance using WIFI log data. Their studies confirmed homophily concerning demographics and academic performance and showed that gender-based homophily increases over time. Boroujeni, Hecking, Hoppe, *et al.* [85] applied SNA modelling techniques to analyse the social dimension and learners' roles on MOOCs discussion forums and their changes over time. Their research found that activity level can be predicted one week in advance based on the course structure, forum activity and properties of the communication network.

Community detection is one of the most significant problems in Social Network Analysis; the analysis of closely linked social groups is one of the comprehensible methods of describing social structures [134]. In higher education, community detection algorithms have been successfully implemented to address varied topics about learning processes. Sturludóttir, Arnardóttir, Hjálmtýsson, *et al.* [137] identified fields of interest in the courses offered in undergraduate programmes. Xu, Lynch, and Barnes [86] analysed discussion forum data of MOOCs courses to gain insights on the creation of social structures and how they change over time. Finally, Yassine, Kadry, and Sicilia [138] used community detection algorithms to study users' engagement patterns on online learning networks.

4.2.3 Learning style, study patterns, and study profile

Learning style theories are used in an educational context to improve learners' learning strengths and instructors' teaching abilities. EDM methods have been used to investigate learning styles [59]. Ahmad and Tasir [139] used log files of online learning activities to analyse the behaviour patterns of engineering students; they concluded that the course structure, students' previous experience, and subject influence the thresholds defined for learning style identification. Costaguta and Angeles Menini [140] studied the relationship between learning style and performance to improve group creation. More recently, Shobbrook, Branch, and Ling [141] implemented elements of EDM to validate the Fedler and Silverman's Index of Learning Styles (ILS) developed for engineering education. In their research, no correlation supporting the validity of the ILS was found, except for lecture attendance. The research about learning styles has been controversial due to the limitations in measuring and determining the learners' learning styles individually [142].

EDM methods are also applied to investigate study patterns in varied contexts. Shirvani Boroujeni and Dillenbourg [143] research presented a data-driven approach to identify and trace study patterns in an unsupervised manner and a hypothesis-driven approach to extract predefined patterns from learners' interactions. Casey and Azcona [144] used the student activity pattern for early detection of poor performers and to identify topics that the students found less interesting or more difficult to understand. Regarding using SNA to investigate study patterns, Lee, Chae, and Natriello [92] analysed clickstream data using hierarchical clustering analysis to identify behaviour patterns concerning the use of a video discussion platform. They analysed the transition pattern between consecutive activities in a video discussion platform.

Considering the difficulties related to the individual identification of learning styles, this paper applies Social Network Analysis and community detection methods to analyse the undergraduate students' study profiles. For our purposes, we define the study profiles through a set of attributes related to educational values, goals, self-efficacy perception, and teaching methods preferences. Our approach relies on homophily to explore the characterisation of the study profiles by analysing the structure of the student community instead of focusing on the individual characteristics of each student.

4.3 Methods

4.3.1 Data set

The data in this study were collected from an online survey distributed to 717 undergraduate students enrolled in the four computer science bachelor programmes at Reykjavik University; BSc Computer Science, BSc Computer Science research-based, BSc Software Engineering, and BSc Discrete Mathematics and Computer Science. The survey was created and distributed in 2019, before the pandemic. It included 42 questions related to institutional support, educational values, goals, self-efficacy and academic apathy, based on a students' readiness survey, the Academic Readiness Questionnaire [145]. The survey was initially distributed to study and understand undergraduate students' learning patterns and behaviours. The Cronbach's alpha coefficient of this questionnaire in this sample is 0.70, indicating good internal consistency reliability [146].

Among the 42 questions included in the survey, the first two questions asked for age and gender. Questions three to five were related to Institutional support; the students were asked about the amount of information they had regarding the university, their degree programme and their career possibilities. In questions six to eight, the students' educational values were evaluated; to measure the priority degree assigned to the university studies and the grades obtained. The following ten questions were goal-related; in this section, the students were asked about their drivers for goal definition, organisation, learning behaviour, methodological preferences, and long-term expectations. The following twelve questions addressed the student's self-efficacy perception; expected performance, skills and abilities, self-motivation, confidence and capacity of adaptation were addressed in those questions. In the next section, academic apathy was measured in four questions asking for the student's effort, work avoidance, and scheduling level when planning their study sessions. The following seven questions were related to the university teaching methods, their preferences about attendance to lectures and practical sessions, as well as honours achievements. The last three questions were about the students' willingness to work in groups and their social network size. Except for age, gender and honours achievement, the questions' answers were on a 5 point Likert scale. Additionally, the students were asked to provide the list of students they most communicate with at the university; the maximum length of the list was 10. The survey's response rate was 38%, with 273 students answering it. Nonetheless, among those responses, only 218 students provided a list of connections at the university.

In the light of the COVID-19 pandemic and the sudden change to Emergency Remote Teaching (ERT) [50], and in line with recent research developed to analyse and understand its impact on teaching and learning processes, we decided to use the data obtained from the survey previously implemented to analyse the preferred study style of Computer Science students before the pandemic, to understand the impact of ERT in the undergraduate student community. Questions in Table 4.1 were selected to perform pre-pandemic study profile identification; these questions relate to the self-perception of motivation, adaptation to different teaching styles, preference to attend or not to lectures, and their willingness to work in groups instead of working alone. The list of students with whom the respondent communicated at the university was used to build a social network of students by creating a link between the respondent and everyone that they named. The data pre-processing was performed in R and Rstudio, while the Social Network Analysis and community detection were performed in Python with NetworkX.

4.3.2 The Girvan-Newman algorithm

The Girvan-Newman algorithm was used to identify the communities in the student network. This algorithm successively removes the edges with the highest betweenness as those edges tend to connect different clusters [134]. Betweenness is a centrality measure helpful to identify the most influential people in a social network. To calculate it, the times a node (edge) is crossed by the shortest path between any other pair of nodes in the network are quantified. The higher the betweenness coefficient, the more essential the node (edge) is to connect with the rest of the network [147]. The Girvan-Newman algorithm returns a set of partitions where each of them represents the clusters identified from the connected components after each edge is removed. As there is no natural benchmark for the identified clusters, each partition returned by the algorithm was evaluated in its modularity to select the partition that maximizes it. The modularity coefficient compares the edges among nodes in the same cluster and the edges among nodes belonging to different clusters [136].

4.4 Results

4.4.1 Network description

Nodes in the network represent a student who either answered the survey or was mentioned by someone who did. Directed edges were created from the student (source) who mentions another student (target). Questions' answer values were included as node attributes in the network. The final network displayed in Figure 4.1 includes 615 nodes with 806 edges. About 22% of the students who answered the survey did not provide a list of friends at the university. Those students, 59 in total, are included in the network as singletons representing 9.5% of the total nodes in the network. There are several reasons explaining the singletons: (1) the students do not have connections in the university, (2) the students do not feel comfortable sharing information about their connections, or (3) as the survey was not mandatory, the student skipped the last part of the questionnaire.

The density and the clustering coefficient are measures commonly used to describe the structure of a network. The density is defined as the fraction of

Table 4.1: Questions selected to perform study profile identification.

Topic	**Question/Statement**
Individual background	Age in years
Individual background	Gender
Educational values	Getting good grades is important to me
Goals	I'm a very methodical person
Self-efficacy	I can easily adapt to different styles of teaching
Self-efficacy	I can motivate myself to study when I need to
University teaching methods	I like the way of teaching (the methods) used at the university
University teaching methods	I do not usually attend lectures at the university
University teaching methods	I watch the lectures online, on Echo360 in Canvas, rather than attend class
University teaching methods	I always attend problem solving classes
Social networks	I prefer to work in groups (arranged by the teacher), rather than work on my own
Social networks	I prefer to work in groups (chosen by students), rather than work on my own

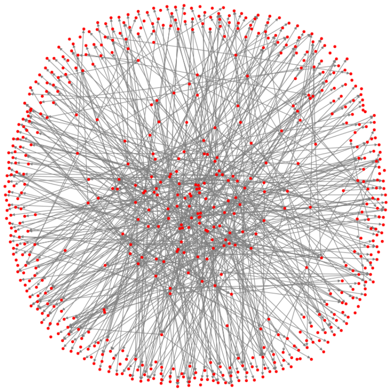


Figure 4.1: Friendship Network of undergraduate students.

connected nodes among all the possible pairs in the network. With a maximum value of 1, the higher the value, the more connected the network is [136]. The average clustering coefficient measures, on average, the extent to which the neighbours of each node in the network link to each other [148]. Both measures are helpful to outline characteristics of the network, such as its completeness and connectedness. The friendship network constructed has a density of 0.00213, and its average clustering coefficient is 0.1213. Networks with low density are told to be sparse; real-world networks are commonly characterised by sparsity [136]. Real-world networks with comparable densities coefficients were found in yeast protein interactions (2,277 links and a density of 0.001) and US air transportation data (18, 617 links and a density of 0.004) [136]. An assortative network is defined by [149] as networks with "a preference for high-degree vertices to attach to other high-degree vertices". The assortativity coefficient of a network is calculated as the correlation among the degrees of each pair of nodes in the network. Networks with positive coefficients are known as assortative, whereas negative values lead to disassortative networks [136]. With an assortativity coefficient of 0.24, we can say this network is assortative; students with many connections tend to frequent other students with a high number of connections. The network has 94 connected components, the biggest with 358 nodes, while the smaller ones are singletons.

Figures 4.2 and 4.3 display the in-degree and out-degree distribution of the nodes in the network. The in-degree value represents the number of times the student appears in others' list of connections, whereas the out-degree is the number of friends or connections declared by each student. The in-degree dis-

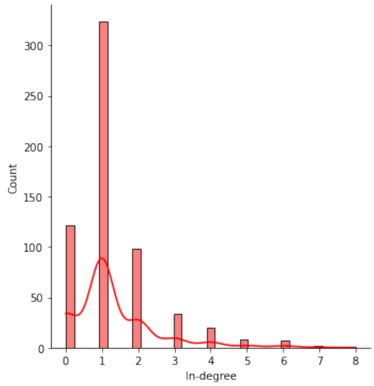


Figure 4.2: In-degree distribution.

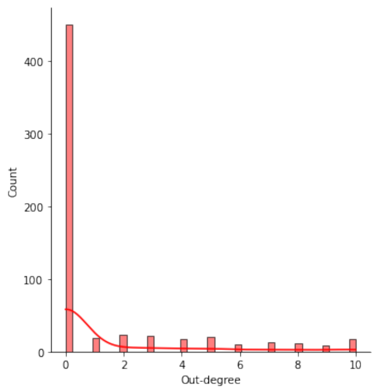


Figure 4.3: Out-degree distribution.

tribution is right-tailed; most students have a low in-degree (are mentioned by fewer people) than the maximum in-degree of the network who has an in-degree of 8. For the out-degree distribution, most of the nodes have an out-degree of zero. The reason for that is, among the 615 nodes in the network: (1) only 273 answered the survey, those nodes that were mentioned by someone but did not answer the survey will have out-degree zero; (2) among those who answered, 59 were singletons with no connections. Figure 4.4 displays the distribution when the zero out-degree nodes are not considered. It is remarkable the number of nodes with a high out-degree.

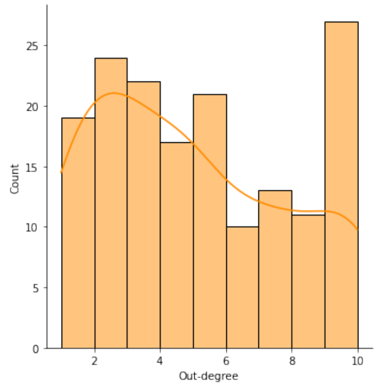


Figure 4.4: Out-degree distribution for degrees greater than zero.

4.4.2 Community detection

The directed network was transformed into an undirected network before applying the community detection algorithms. With this change, the final amount of edges decreased to 739, and the average degree of the nodes is 2.40. Figure 4.5 displays the modularity coefficient for each of the partitions returned by the Girvan-Newman algorithm, the partition with the highest modularity, 0.89, has 110 communities. The number of communities is high due to the 59 singletons in the network; each singleton is a single community. We analyse the attributes of the five largest communities and present their preferred study profile. The communities were named ‘Star pupils’, ‘Independent students’, ‘Team players’, ‘Female power’, and ‘Versatile students’. In those communities, 162 students are included. Figure 4.6 displays them coloured by the community they belong to. ‘Star pupils’ is the only community disconnected from the others. In the following subsections, the study profile that characterises the communities will be outlined based on the distribution of the answers to the attributes in the Academic Readiness Questionnaire [145] in Table 4.1. Figures 4.7 and 4.8 display the average and median of the responses to each question by converting the Likert scale into: Strongly Agree=5, Agree=4, Neutral=3, Disagree=2,and Strongly Disagree=1.

Community No. 1: ‘Star pupils’.

The first community identified includes 35 students. Among them, 69% are males, 20% female and 11% unknown. The response rate of the students in this community is 37%.The study profile is characterised by:

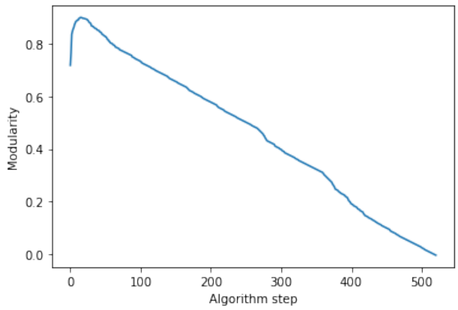


Figure 4.5: Modularity coefficient in each step of the Girvan-Newman algorithm.

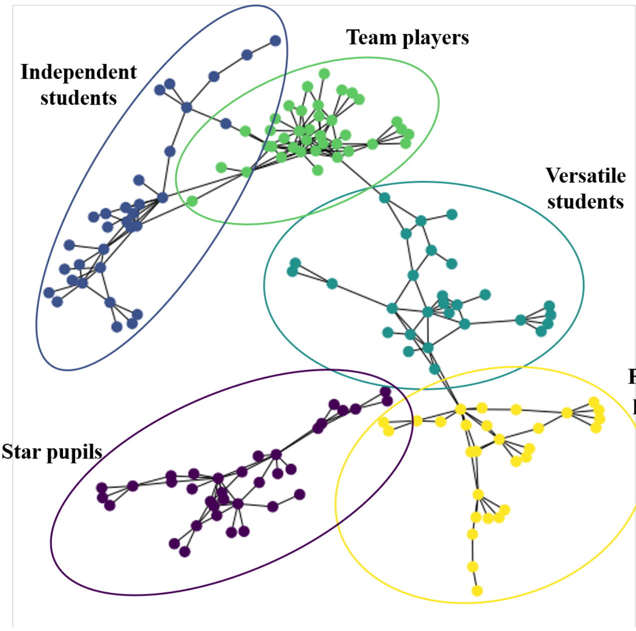


Figure 4.6: The five biggest communities identified using the Girvan-Newman algorithm.

- Its members are mostly younger than 22 years.
- They declare that getting good grades is important to them.
- They are highly methodical, and they can highly adapt to different styles of teaching.

- They also declare being always able to motivate themselves when needed.
- These students also say they do like the teaching methods at the university.
- They always attend lectures, and they prefer to attend rather than to watch recordings. They always attend practical classes.
- These students prefer to work alone rather than working in groups arranged by the teacher.

Community No. 2: 'Independent Students'

This community includes 32 students. The gender distribution is quite different from the first community analysed; 56% males, 38% females, and 6% unknown. In this community, the response rate was 38%. The study profile of this community is featured by:

- Most of the students are around 25 years old, but the ages range from 23 to 38.
- Getting good grades is important, but they are not very methodical.
- They declare they could adapt to different teaching styles, but they mostly like the teaching methods at the university.
- What makes this community special is that they do prefer to watch the lecture recordings.
- Finally, this community prefers to work in groups chosen by themselves rather than working alone.

Community No. 3: 'Team players'

This community consists of 38 students. A 63% of them are males, 20% females, and 8% unknown. Similar to the previous communities, its response rate is 40%. Among its features is possible to identify:

- The students are around 23 years old, with ages from 20 to 26 years.
- Getting good grades is important, and they declared themselves to some extent methodical.
- They agree they can adapt to different teaching methods, and they mostly like those used at the university.
- The students usually attend lectures at the university and also problem-solving classes.
- In contrast to the other communities, these students do prefer to work in groups chosen by themselves rather than working alone.

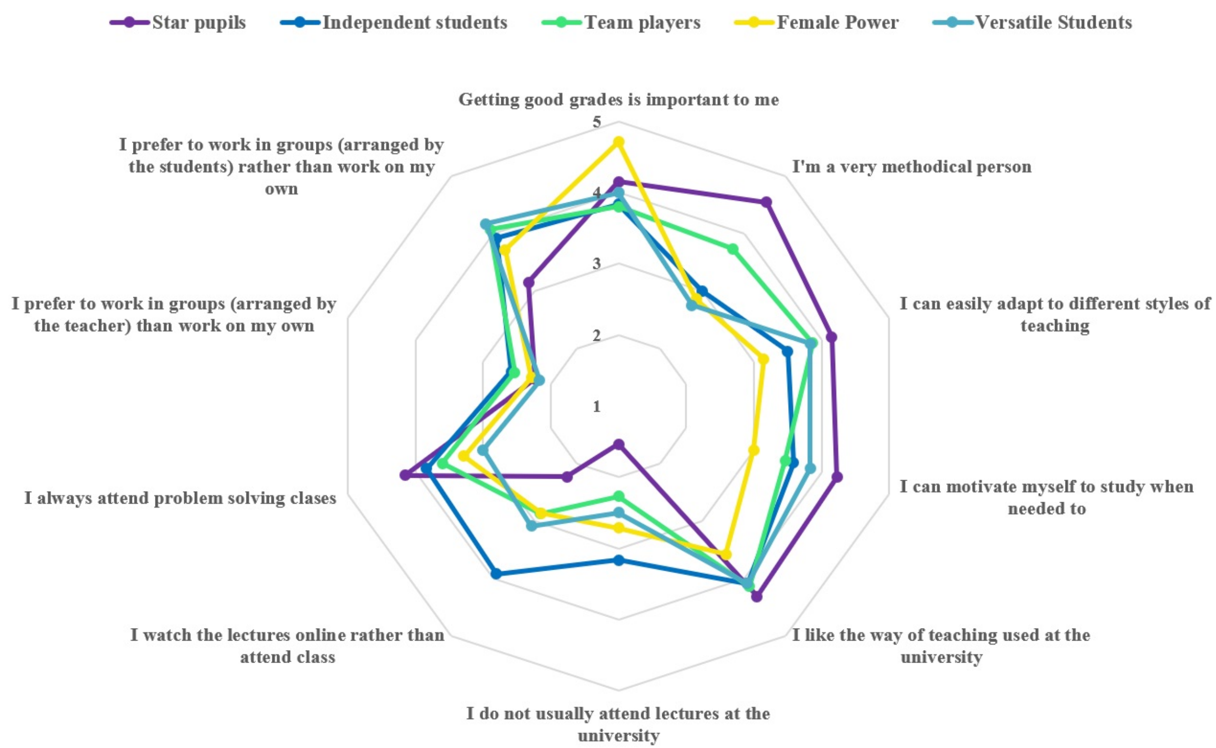


Figure 4.7: Average responses of the communities based on the Likert scale: Strongly Agree (5), Agree (4), Neutral (3), Disagree (2), Strongly Disagree (1).

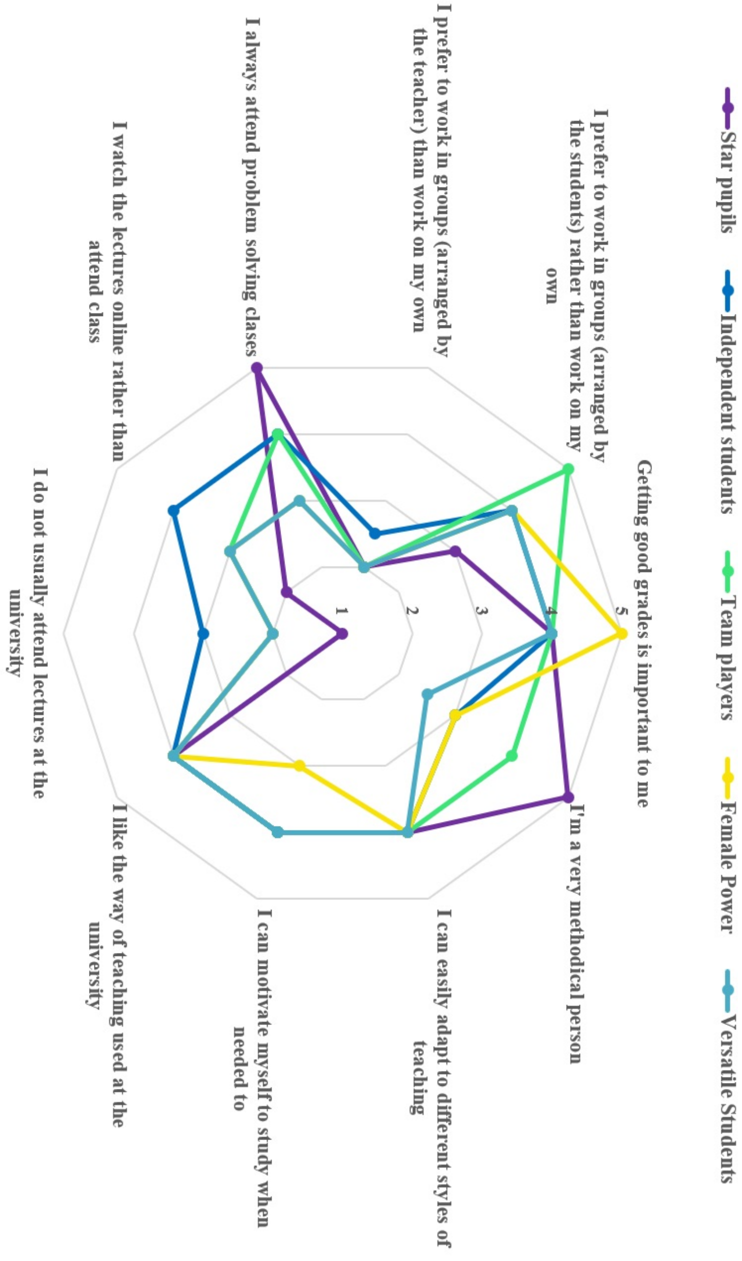


Figure 4.8: Median of the communities' responses based on the Likert scale: Strongly Agree (5), Agree (4), Neutral (3), Disagree (2), Strongly Disagree (1).

Community No. 4: 'Female Power'

This community has 29 students. It is the only community with a higher percentage of females, 55%, whereas 34% are males and 10% unknown. Additionally, this community has the lowest response rate among the five communities analysed, 24%. The features characterising this community are:

- Their age goes from 20 up to 30 years with a uniform distribution.
- In this community, getting good grades is essential.
- They declare they could adapt to different teaching methods.
- In addition, they could prefer to work alone rather than in groups chosen by the teacher, but also prefer to work in groups rather than alone.

Community No. 5: 'Versatile Students'

Twenty-eight students are allocated to this community. It is the community with the highest percentage of males, 82%, while 7% are females, and 11%unknown. The response rate was 42%. This community shares most of its features with the previous communities presented:

- Its members are around 27 years old.
- Grades are important, and they declare to be able to adapt to different styles of teaching.
- They declare themselves to be able to motivate themselves when needed and mostly like the teaching methods at the university.
- These students attend lectures almost always.
- Regarding group work, they prefer to work in groups chosen by themselves, or alone if the groups are chosen by the teacher.

Singletons

There are 59 singletons in the network, most of them are less than 30 years. The gender distribution is similar to the distribution of the whole network; almost 65% are males. Among their features; getting good grades is important to them, but there is no evident definition of being methodical when studying; they could adapt to different styles of teaching, motivate themselves when needed to, and they like the teaching methods at the university; regarding attendance to lectures, the distribution of the answers is uniform among the statements, but most of them agree on prefer watching the lecture recordings instead; finally, regarding group working, there is no clear definition when the teacher chooses the groups, but they tend to slightly prefer to work alone rather than groups chosen by the students themselves.

4.4.3 Statistical comparison of attributes' distribution

Differences among the distribution of the communities' attributes were evaluated using the Kruskal-Wallis test. Only four attributes showed differences in their distributions considered statistically significant; (i) Question 4 in Table 4.1: *Being methodical*, (ii) Question 5 in Table 4.1: *Adaptation to teaching styles*, (iii) Question 8 in Table 4.1: *Lecture attendance*, and (iv) Question 9 in Table 4.1: *Watching recorded lectures*. Among those attributes, the community 'Star pupils' has significant differences in *Being methodical* from 'Independent students', 'Versatile students', and 'Female power' communities. Regarding *Lecture attendance* and *Watching recorded lectures*, a significant difference was found between 'Star pupils' and 'Independent students'. In contrast, for *Adaptation to teaching styles*, a significant distribution difference was found between 'Star pupils' and 'Female power'.

4.5 Discussion and conclusion

This study presents five different study profiles among the undergraduate students in the Computer Science Department at Reykjavik University. The data were gathered from an online survey distributed in 2019 as an initial approach to understanding undergraduate students' learning patterns and behaviours. Relevant features of the student network in this university before the pandemic are; students with many connections tend to interact with other students who also have many connections, but also, the network has a high percentage of singletons, students without connections. As the second step in this analysis, the Girvan-Newman algorithm was used to identify the communities; the optimal partition was selected based on its modularity. The largest communities were analysed to identify the features and learning preferences that characterise the study profile of its members. In the third section, we identified five communities with an evident and particular profile. (1) 'Star pupils' is featured by being those who always behave as expected and have many of the *best* attributes. Being the community with the youngest members (mostly less than 22 years), first-year students are likely allocated to this community and keeping most of the study habits they used to have at high school. (2) With students slightly older than the first community presented (around 23), 'Team players' members consider the group work an essential factor in their learning preferences, as long as they can choose their groups. (3) The third community, 'Independent students', has students around 25 years. This community is featured by preferring lecture recordings instead of always being at the university's venues. (4) 'Versatile Students' community has, on average, the oldest students (around 27 years). This community share features with the previous communities. From the first four communities, we can infer that the year of study and maturity level play an important role in determining the study style profile and preferences. As the students move on in their undergraduate studies, they become able to adapt their learning strategy to the needs and requirements of each course, presumably more complex in the last terms of their studies, becoming a 'Versatile Student'. Last but not least, the fifth community, 'Female Power', is characterised by being the only community with more females than males. In line with the results obtained by Nguyen, Poquet, Brooks, *et al.* [89] gender-based homophily is present. Nevertheless, besides gender, the attribute that features this community is how important getting good grades is. Regarding singletons, most of them prefer lecture recording, and as it could be expected, they prefer working alone; if the teacher or the students choose the groups, it does not matter.

The sample of the students examined in this paper falls under STEM, which stands for Science, Technology, Engineering and Mathematics. Within the literature on STEM, there has been an ongoing discussion on the issues related to students' sense of belonging. On that note, an extensive body of literature has focused on solutions targeted towards developing an increased sense of belonging, which is thought to lower the impact of identity-related issues on education; one such identity-related issue can be due to skewed distribution between genders in STEM [150]. This paper is a contribution to that literature through the five communities.

Among the limitations of this study, the data was gathered with an online survey. It does not allow linking the students with the average grade, the number of credits earned, or the year of study. That information could be helpful to analyse how the communities evolve through the years, to what extent the students interact with and provide support to peers from other years, and how the study style selection relates to academic performance. Other drawbacks of this data collection method are the (i) response rate [151], affecting the performance of the Kruskal-Wallis tests due to small group sizes and (ii) response biases related to social desirability and the tendency to always select extreme ends in the Likert scale [91]. Regarding the sample used in this analysis, the students surveyed belong to the Computer Science Department; students in other departments may have different study styles, so the identified communities' presence should not be generalised to students in other departments. This paper focused on the biggest communities; 30% of the students with at least one connection are part of the communities and profiles presented. Therefore, the other communities should be analysed to identify if their study profiles are similar to those identified.

The results regarding the profiles of undergraduate students lead to relevant implications and future work. Before the pandemic arose, only one of the five identified study profiles preferred lecture recordings over the university venues. The students in the community 'Independent students' could have fewer difficulties during the ERT as they had previously interacted with the lecture recording platform. In contrast, most students were used to attending face-to-face lectures, and their transition to distance learning could be more complicated. Furthermore, the impact of the forced distance learning period could be bigger for the youngest students, 'Star pupils', as they highly prefer university venues. Another affected community was 'Team players', who highly valued interacting with their peers; during the pandemic, their interactions were limited due to the pandemic restrictions to contain the spread of the virus. Recent studies on the effects of the pandemic in education provide insights into how the new normality in higher education will be [129], [152]–[154]. On one side, the use of digital technology[2] and the transition to hybrid learning are expected to be present in the new normality of higher education [153]. In contrast, the impact of ERT on the students' experience with online learning may modify their preferences about enrolling in online courses in the future [152], [155]. The communities and study profiles analysed in this study correspond to the pre-pandemic period. Consequently, once the pandemic finishes, it is essential to study and understand the changes in the learning profile and preferences of the students in the communities highly affected by the ERT. Furthermore, understanding to what extent the pre-pandemic communities' structure remained or not after the pandemic will allow redesigning teaching strategies to provide better support to the students according to their specific profiles.

The past term, Spring 2021, ran still with restrictions due to the COVID-19 pandemic. Most of the schools around the world remained closed. The term Autumn 2021 will be, maybe, the first term of education adaptation after the pandemic. Future work of this research relates to analysing the undergraduate students' new connections, study profiles, self-efficacy perception, and goals during the adaptation to a new normality in higher education. In addition, other university departments and other data sources, such as data generated from LMSs or external tools, such as forum activity or recorded lectures, will be included to enrich the SNA and student communities' profiling. The integration of those data sources will allow linking the results obtained in this study with similar research performed using SNA on LMSs data, making our conclusions more generalisable. Finally, more research is also needed in investigating the evolution of students' social networks through their years of study at the university and how their modifications relate to their study profile and performance.

[2]Referred to as 'technology' in the published manuscript [1]

Chapter 5

Making the Most of Slides and Lecture Captures for Better Performance: A Learning Analytics Case Study in Higher Education

The provision of educational material in higher education takes place through learning management systems (LMS) and other learning platforms. However, little is known yet about how and when the students access the educational materials provided to perform better. In this paper, we aim to answer the research question: *How do the high achievers use the educational material provided to get better grades?*. To answer this question, the data from two educational platforms were merged: a LMS, and a lecture capture platform. We based our analysis on a series of quizzes to understand the differences between high and non high achievers regarding the use of lecture recordings and slides at different moments: (1) before and (2) while solving the quizzes, and (3) after their submission. Our analysis shows significant differences between the groups and highlights the value of considering all the educational platforms instead of limiting the analyses to a single data source.

5.1 Introduction

Educational material, e.g., slides and lecture captures, has been widely used in educational settings to support teaching and learning practices. They have several benefits for both teachers and students, and over the past two years, they have been cornerstone elements driving and supporting distance learning modalities during the pandemic. With the increase in the number of learning platforms used for delivering educational content by providing learning material to the students, higher education institutions might face difficulties to identify which learning platforms the students find more engaging or supportive for their learning processes compared to those less beneficial [14], [156]. Furthermore, little is known to date about how students use the learning materials provided to support their own learning process while studying and solving assignments.

This paper focuses on analysing undergraduate students' activity related to the use of educational material to understand how the students use it to support themselves and perform better. In particular, we are interested in knowing the differences between 'high achievers' and 'non high achievers' regarding the use they make of slides and lecture captures. Through our analysis of the students' activity, we aim to answer the following research question: *How do the high achievers use the educational material provided to get better grades?* To that end, the analysis focuses on one undergraduate course taught in Spring 2022 to 59 students, and their interactions with the educational material related to solving a series of nine class content related quizzes. Two data sources that provide insightful information about undergraduate students' learning behaviour are combined and analysed for the purpose of this paper; the learning management system where the students had access to the slides, and a lecture capture platform where they could access both the lecture recordings and the slides. We perform a two sided analysis, studying lecture capture activity and slides activity.

Our findings show that high achievers tended to make better use of both learning platforms as the course progressed. In contrast, non high achievers showed lower engagement levels, especially with the lecture capture platform.

The rest of this paper is organised as follows. In the next section, we discuss related work on learning analytics self-regulation research. In Section 5.3 we present the methodology used in this research, followed by the results in Section 5.4. The paper concludes with a discussion on the implications and limitations of our work and directions for future work.

5.2 Related work

5.2.1 Learning analytics and students' self-regulation

The education provision in higher education institutions relies on several educational platforms, such as Learning Management Systems (LMSs), e.g. Canvas, Moodle, or Blackboard; and other interconnected external learning platforms, e.g. discussion forums, lecture recordings, coding platforms, etc. [14], [107]. Those platforms not only facilitate the students' access to the learning material, they also provide flexibility for the students to learn at more convenient times by providing on-demand access to those materials, meaning the students' physical attendance to the lecture rooms is no longer needed [129]. Furthermore, since the pandemic started, the education provision was significantly modified to meet the students' and teachers' needs, and traditional teaching methods were adapted to meet new distance, blended and hybrid modalities [157].

The aforementioned platforms capture and store the students' detailed activity within the platform elements and modules; as well as the students' interactions with the learning materials provided by the instructors. In consequence, large data sets of time stamped clickstreams -or digital traces- are produced, providing insights into educational practice [32]. The massive amounts of educational data and digital traces from LMSs and interactive learning environments are a common source of data in learning analytics research and have been widely used with the objective of investigating several elements of learning and teaching processes [96], [97]. Previous research based on these data has highlighted learning platforms' data are a helpful resource that allows to investigate the students' engagement, self-regulation, and time management skills [98]–[100].

Self-regulated learning has been defined as a process that involves four recursive stages: (i) task definition, (ii) goal setting and planning, (iii) enacting study tactics and strategies, and (iv) adaptation [53]. This model of self-regulated learning defined by Winne and Hadwin [53] has been extensively adopted in computer supported learning environments [101]. In this model, given a learning task; (i) and (ii), involve the students' task understanding, and their plan for addressing it, respectively. For the purposes of this paper, this case study focuses on (iii) and (iv). In (iii), the study tactics and strategies selected based on (i) and created in (ii) are implemented, whereas in (iv) the students change their learning strategies based on the experience and evaluation elements. Several indicators based on learning platforms clickstream have been created to analyse self-regulation behaviours, to build dashboards, and inform both learners and instructors [102]. Some examples of those indicators are the students' level of engagement, time utilisation, posting activity, etc. In the following subsections, we present related work on self-regulation and learning strategies based on data gathered from LMSs and lecture captures, the indicators created, and the main results obtained from the analysis of those indicators.

5.2.2 Leaning management systems' clickstream data

Previous research has confirmed that activity indices from LMSs' web logs provide a reliable representation of learner behaviour [158] and student engagement [100] in varied learning environments. Joksimović, Gašević, Loughin, *et* *al.* [159] used trace data to examine the effect that the number and duration of four interaction types had on the students' final grades. Their results indicate a positive correlation between grades and the interactions of the student with the learning platforms provided. Sher, Hatala, and Gašević [99] used LMSs clickstream data to study consistency patterns in blended courses by identifying five student clusters based on the students' grades, consistency in discussion forum activities, and consistency in assignments activities. Their research highlights the need for investigating the consistency of study patterns over time. Similarly, Jovanović, Saqr, Joksimović, *et al.* [98] included logs from the LMS in discussion forums, the main course page, grades and learning materials views to study the association between academic achievement and the students' engagement with the learning activities. In their studies, the time spent online, consistent contributions to discussion forums, and regular access to the learning material were significant predictors of high academic achievement.

Recently, researchers have focused on analysing how and when the students interact with the LMSs and its content, as well as the relationship between the interactions' time and the students' academic performance. Sher, Hatala, and Gašević [160] investigated the differences on when the students interacted with the LMS using three different types of electronic devices. Their research shows the students generally use two or more types of devices to access the course content, and significant variations were found on the time they prefer to use each of them. Saqr, Nouri, and Fors [123] and Saqr, Nouri, and Fors [124] focused on analysing the temporality of student engagement actions. They based on LMS time stamped data to study the differences in engagement patterns between high and non high achievers at different moments during the day, week, course, and year. Their research shows that despite both high and non high achievers tend to decrease their activity levels as the course progressed, their interaction patterns were significant predictors of academic achievement. Accordingly, the authors highlight the importance of further investigating time as an indicator of how the students self regulate their learning. In this paper, we contribute to that call.

5.2.3 Lecture capture viewing data

Lecture captures have several benefits for students and teachers, their provision promotes independent study, attendance flexibility, and time management skills acquisition [129]. The data provided by such lecture capture platforms have been extensively investigated, providing important insights into teaching and learning practices. For example, Rodriguez, Lee, Rutherford, *et al.* [161] focused on identifying self-regulated learning patterns based on indicators of video completion and time management. In their research, the clickstream data were used to count the students' clicks on the pre-recorded videos provided by the teacher, classified based on their time-stamps, and used to identify four types of self-regulated behaviours. Edwards and Clinton [162] analysed how the students used the lecture recordings. They found the students used the lecture captures as a substitute for attending live lectures. This constitutes one of the main instructors' concerns regarding the use of lecture capture platforms to complement the learning environment because such a choice has implications on the students' levels of attendance to live lectures and verbal engagement [163]. Nonetheless, it has been found that the preference for utilising lecture recording platforms against attendance to live lectures is correlated with the students' learning profiles and as well as their previous experience using the particular learning platform [1]. Consequently, there is a growing need of examining lecture capture platforms in general and the use of lecture recordings in particular in varied educational settings to gain a better understanding of the way the students learn and benefit from their use [163].

5.3 Methods

5.3.1 Data sources

This study encompasses data from two data sources: (1) a learning management system (LMS), and a (2) lecture capture platform. The data from Canvas, which is the LMS, were accessed through several reports from the LMS itself and its connected Application Programming Interface (API).

Regarding the lecture capture platform, the data were gathered from Echo360 [164]. The lecture capture platform is available to all teachers at the university to create and deliver educational material and likewise, all students, are also enabled access to it. Similarly to the LMS reports, the data were gathered from the Echo360 API. The reports included from these data sources are described in Table 5.1. All students enrolled in the course were active in both learning platforms.

5.3.2 Course structure

The course selected was Data Analysis; it is an elective course offered to second and third year students enrolled in any undergraduate program within the Department of Computer Science. In the term Spring 2022 the course had 59 students enrolled. The minimum grade to pass undergraduate courses at Reykjavik University is 50 out of 100 points. The course's assessment comprised five coding assignments (20%), the mid-term exam (20%), nine quizzes (20%) and the final project submission and presentation (40%). The only element in the assessment structure that was meant to be fulfilled in groups was the final project. The five coding assignments were handed in and graded in an

Table 5.1: Reports from the LMS (Canvas) and the lecture capture platform (Echo360) API included.

Platform	Report	Description
LMS (Canvas)	Students	List of enrolled students' names, user ID's, and login ID's.
	Modules Items	List of all elements in the modules section, title, content IDs, and URLs.
	Assignments	List of all course assignments (Title and ID's), deadline, and points.
	Assignments submissions	Detail of student submissions, submission time, and score.
	Quizzes	List of all course quizzes (Title and IDs), question count, and points.
	Quizzes submissions	Detail of student submissions, start time, finish time, and time spent.
	Page views	Detail of pages' views in all components in the LMS, user IDs, and URLs.
	Grades	List of enrolled students' login IDs, and final course grade.
Lecture capture platform (Echo360)	Section	Course ID, Course Name, Instructors login IDs, and LMS course ID.
	Lessons	List of all course lessons, names, time, and live stream indicator.
	Video views	Weekly report of video watching activity: login ID, timestamp, video Id, video name, and duration.
	Presentations	List of presentation events, IDs, timestamp, and student login ID.

external learning platform for coding collaboration, and the interactions within that learning platform are not analysed as a part of this paper. Regarding the quizzes, they were embedded into the LMS with a fixed unlocking time for all students and that data therefore outlines an important element in our analysis. The quizzes were automatically graded through the LMS, and only the highest seven scores were counted for the final grade.

The course was taught for 11 weeks with two lectures and one practical session per week. During the first five weeks, the course lectures were pre-recorded by the teacher and uploaded to the lecture capture platform Echo360 in advance. This was done because of restrictions due to the covid-19 pandemic. In addition to the recordings, the teacher established drop-in sessions to solve questions related to the lecture recordings. During these five weeks, 16 recordings were provided to the students, allowing them to get used to the lecture capture platform and its features. For the remaining six weeks, the lectures were on-site at the university premises, but live-streamed through Echo360, recorded and uploaded afterwards into the lecture capture platform. This structure provided the students with the flexibility to choose whether they would prefer to attend the lectures in person, to watch them live, or to watch the recording at a more convenient time for them. During these latter six weeks, a total of ten lecture captures were uploaded to Echo360. Similarly to the lecture captures, the slide decks for each lecture were provided by the teacher in both platforms, Canvas and Echo360. Additionally, for each of the first nine live-streamed lectures, the students had to solve one of the quizzes. The quizzes unlocked automatically once the lecture started and their deadlines were fixed at midnight on the same day. However, late submissions were allowed and the students could take as much time as they needed to solve them and submit their final answers without a grade penalty. Despite that, most of the students solved their quizzes “on time”. However, as it could be expected given that only the highest seven grades were taken into account towards their final grade, the last two quizzes were those with the highest number of students with “missing” submissions (See Figure 5.1).

5.3.3 Analysis

The aim of this study was to understand how the students used the slides and lecture recordings to perform better. Accordingly, we decided to focus on analysing the students’ activity related to solving the nine quizzes and its relationship with the final grade obtained in the course. The level of significance for all statistical tests computed was set at 0.05. The correlation coefficient between the quizzes and the final grade is $\tau = 0.669$ (See Figure 5.2), indicating the quizzes are a significant component of the final grade. Moreover, the students were classified into high achiever and non high achiever based on

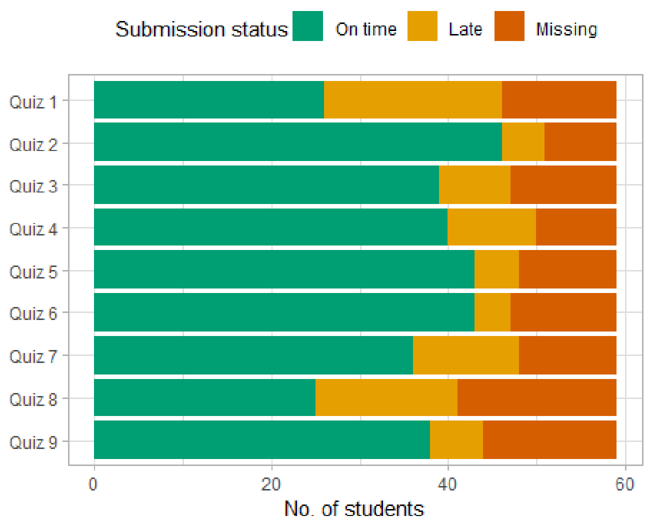


Figure 5.1: Distribution of "on time", "late" and "missing" submissions for the 59 students enrolled.

their final grade. The students with a final grade of at least 80 were classified as high achievers (33 out of 59 students), and as non high achievers otherwise. Only three students got less than 50 points and failed the course.

The reports described in Table 5.1 were combined based on the students' login ID, quiz names, video ID, video name, presentation ID, and presentation name. As the LMS provided exact information about the starting and ending times of quizzes' solving, the students' activity with the educational materials corresponding to each quiz was divided into activity *before* starting the quiz, *during* the solving time, and *after* submitting the quiz. Table 5.2 displays the mean and median values for the final grade, the total points got in the quizzes (out of 41), and the average time spent solving the quizzes.

Table 5.2: Mean and median values split by *high achievers* and *non high achievers*.

Variable	High achiever		Non high achiever	
	mean	median	mean	median
Final Grade	90.4	89.4	60	67.9
Quiz Score	33.9	34.5	17	17.8
Solving time (hours)	4.1	0.3	0.4	0.1

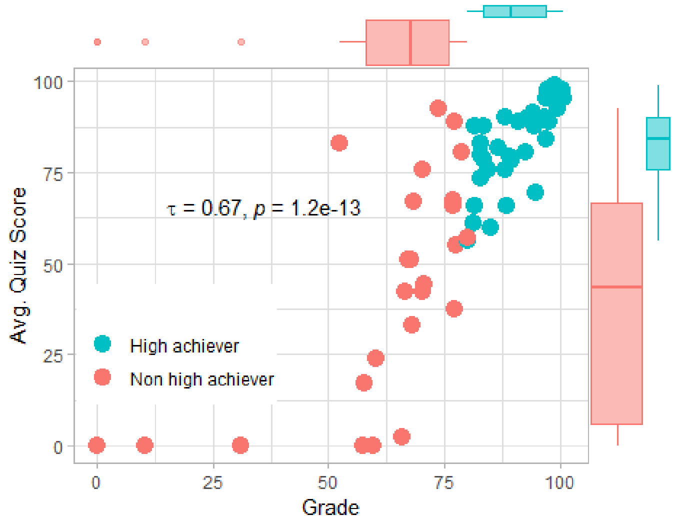


Figure 5.2: Correlation between the average score in the quizzes and the final grade in the course.

5.4 Results

Taking into consideration the sample sizes and variance, Mann-Whitney U-tests and t-tests were used to evaluate for differences in the variables' distribution [165] between high achiever and non high achiever students. Statistically significant differences between both groups were found for grade, quizzes score and solving time. Table 5.3 shows the value of the test statistics and p-values obtained from the statistical tests. As expected, the students classified as high achiever got higher grades at the end of the course and their scores in the quizzes were also higher than non high achiever students. Moreover, the tests also indicate the high achiever students spent more time solving the quizzes compared to the non high achiever students.

Table 5.3: Statistics and p-values for differences in the distribution of *high achievers* and *non high achievers*.

Variable	Statistic	p-value
Final Grade	t=8.8921	2.667e-10
Quiz Score	w = 99.5	4.961e-07
Solving time (hours)	w = 209	0.0007995

5.4.1 Lecture capture activity

The students' watching activity within the lecture capture platform was gathered using the Video views report from Echo360 as described above (Table 5.1). In this report, each entry corresponded to 30 seconds of video watched. Therefore, by aggregating the information provided by the report is possible to compute the minutes watched for each lecture capture. Despite small variations in the lectures' length, the ratio of video watched was computed to allow comparisons between groups and weeks. To identify the differences in the lecture capture usage between high achievers and non high achievers, the watching activity that took place before, during, and after the quizzes' were submitted, was compared in two different ways: (1) Analysing the activity of all quizzes together, and (2) splitting the watching activity by quiz, to look for changes in the usage of the lecture captures as the course progressed.

Results from the Mann-Whitney U-tests displayed in Table 5.4 show there are significant differences between the ratio of video watched before, during and after the quiz submission for the high achievers compared to the non high achievers. Median and mean values for the ratio of video watched in Table 5.5 indicate that on average, the high achiever students watched the lecture captures more than the non high achievers.

Table 5.4: Statistics and p-values for differences in the distribution of lecture capture ratio watched.

Variable	Statistic	p-value
Ratio before	W = 278.5	0.0117
Ratio during	W = 308	0.04478
Ration after	W = 304	0.03261

Table 5.5: Mean and median values for lecture capture ratio watched.

Variable	High achiever		Non high achiever	
	mean	median	mean	median
Ratio before	0.08	0.01	0.04	0.0
Ratio during	0.16	0.01	0.03	0.0
Ration after	0.07	0.0	0.02	0.0

Considering the lectures corresponding to the quizzes content were delivered live and the students were allowed the option to attend in person to them; accessing the lecture capture platform was not strictly needed in order to access the class content or solve the quizzes. For that reason, in addition to the previous plots and tests presented, the following section includes merely the students with watching activity to investigate the differences in their watching patterns and the relationship with their academic performance through the proxy of their grade. Figure 5.3 shows the distribution of ratio watched before, during, and after the quiz submission respectively. It is noticeable that non high achievers watching behaviour differs from the watching behaviour of high achievers.

Similar to the submission patterns identified before, the students' watching behaviour for the last quizzes was distinct from their watching behaviour for the first quiz submissions. For lecture captures watched before (during) non high achievers solved the quizzes, the ratio of videos watched dropped considerably after the first seven (six) quizzes. Regarding lecture captures watched after the quiz submission times, most of the students that were actively utilising and checking out the recordings were high achievers.

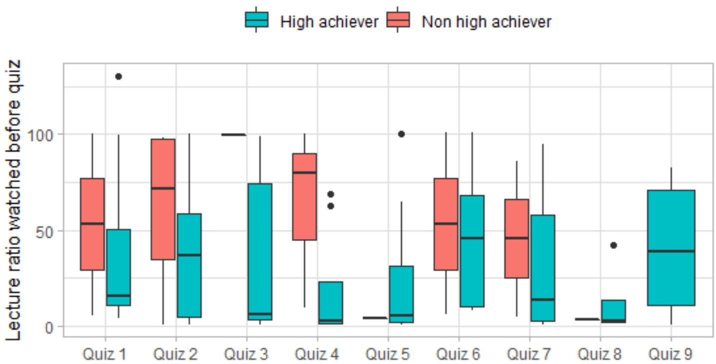
In contrast to non high achievers whose activity dropped for the last quizzes, the high achievers' watching activity before, during, and after was more consistent along the course. However, Figures 5.3b and 5.3c show the high achievers watching activity, despite being more consistent, was not necessarily constant through the course as the ratio of lecture capture watched while solving the last quizzes was higher than the ratio watched during the first quizzes. Contrarily, the ratio watched after the quiz submissions seems to decline as the term progressed. In order to evaluate such changes in the watching behaviour, chi-squared tests for trends in the proportions were computed. The tests statistics were calculated using the median minutes watched out of the total minutes of each lecture capture. The tests results were significant for the ratio during and after the quiz submission (See Table 5.6).

Table 5.6: Test results for trends in the lecture ratio watched by high achievers.

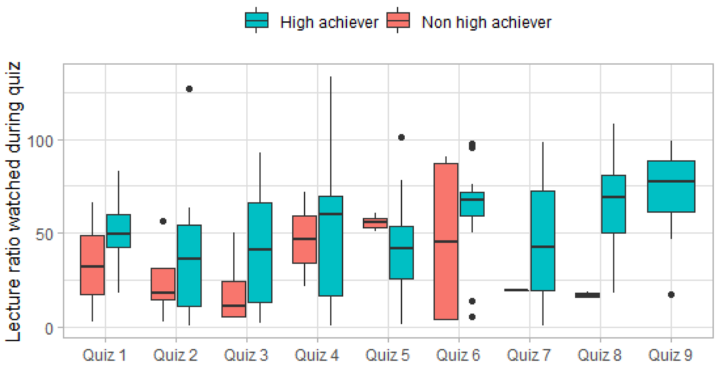
	χ^2	p-value
Before	3.143	0.07622
During	24.752	6.521e-07
After	28.467	9.53e-08

5.4.2 Slides activity

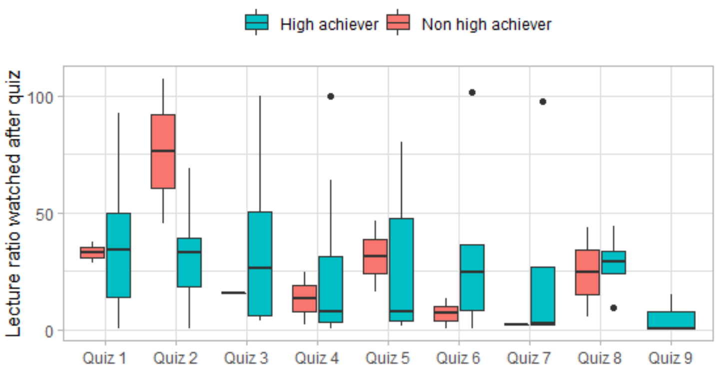
As described in Section 5.3.2, the teacher uploaded the slides related to each lecture to both learning platforms, Canvas and Echo360. As the students could access the slides on any of the learning platforms, both were included in the analysis. However, the structure of the activity reports provided by the platforms and the information contained on them were different. The report *Presentations* from the Echo360 API provided information regarding the stu-



(a) Watched before



(b) Watched during



(c) Watched after

Figure 5.3: Distribution of the lecture ratio watched before (a), during (b), and after (c) each quiz.

dents' engagement with the presentations uploaded by the teacher through the platform. In this report, each row represents one viewing event (one slide or whole slide deck view) of the presentations. In contrast, in the report *Page Views* from the Canvas API, each row represents one of the URLs the student accessed through the LMS. Related to the slides, the data do not only include information on the number of viewing events (whole slide deck) that the students had through the system, but also information related to the number of slide deck downloads.

The slides were widely used by the students throughout the course, 81% of them accessed the slide decks at least once through any of the learning platforms. However, the percentage of high achievers (90%) accessing the slides was significantly higher than the percentage of non high achievers (69%) (χ^2 = 3.18, p-value = 0.03705). To address to what extent the access to the slides changed between groups as the course progressed, the slides activity was split by the quiz the slides belonged to. Figure 5.4 displays the percentage of high and non high achiever students accessing the slide decks for each quiz. Similarly to the watching behaviour addressed above, the percentage of non high achievers accessing the slides of Quizzes 8 and 9 was lower than the percentage for the previous quizzes. In contrast, the percentage of high achievers accessing the slides was much more consistent across quizzes. On average, 75% and 41% of high and non high achievers accessed them respectively. The percentage differences are significant for eight of the nine quizzes. Quiz 3 was the only one without significant differences between groups (Prop-high = 67%, Prop-non = 50%, χ^2 = 1.0546, p-value = 0.1522). Furthermore, Figure 5.4 also displays which learning platform the students used to access the slides. It is noticeable that most of the students in both groups accessed the slides either through both platforms or Canvas exclusively; whereas a limited number of students accessed the slides only through Echo360.

To address the differences in the time the students in each group accessed the slides, the activity was split using the start and end timestamps of each quiz submission. Statistical tests were performed for differences in the proportions before, during and after. Results are shown in Table 5.7. Compared to non high achievers, a higher percentage of high achievers accessed the slides before starting the quiz, while solving the quiz, and after their quiz submissions.

Regarding the slide deck downloads, the difference in the proportion of high and non high achiever students downloading the slides to their personal computers was smaller than the difference in accessing them through the platforms. For high achievers, about 35% of them downloaded the slides at least once during the term, whereas for non high achievers the proportion was 28%. The proportion of students downloading the material for each quiz is displayed in Figure 5.5. Contrary to the differences between groups accessing the slides, for downloading the material no difference was found in the number of downloads

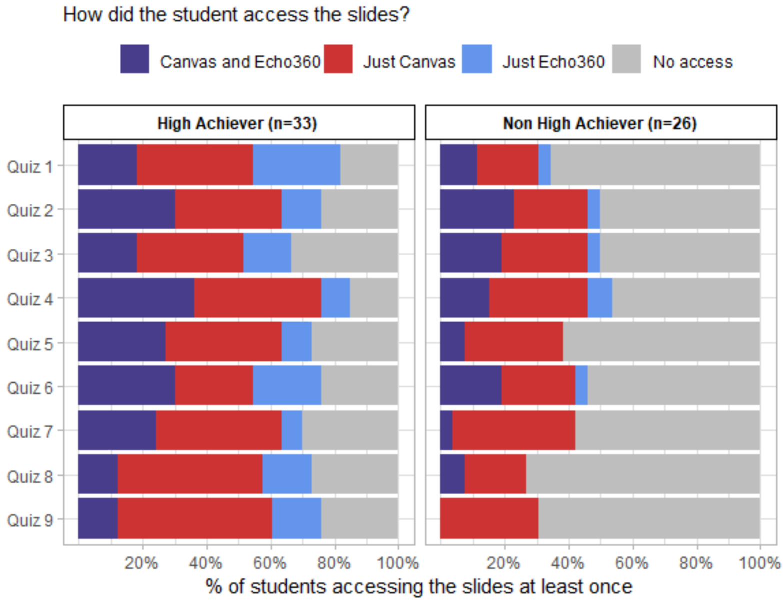


Figure 5.4: Percentage of students accessing the slides. Split by quiz and platform.

Table 5.7: Proportion test results for differences in the percentage of students accessing the slides.

Time	High achiever	Non high achiever	χ^2, p-value
Before	73%	42%	4.38, 0.01
During	90%	54%	8.67, 0.001
After	79%	54%	3.08, 0.039

before, during or after the quizzes' submission times. Nevertheless, most of the downloads for both groups took place while the quizzes were being solved, indicating those students also used the slides to support themselves and perform better.

5.5 Discussion and conclusion

This research delves into students' use of lecture captures and slides to get better grades. As presented in Section 5.2, several indicators based on the stu-

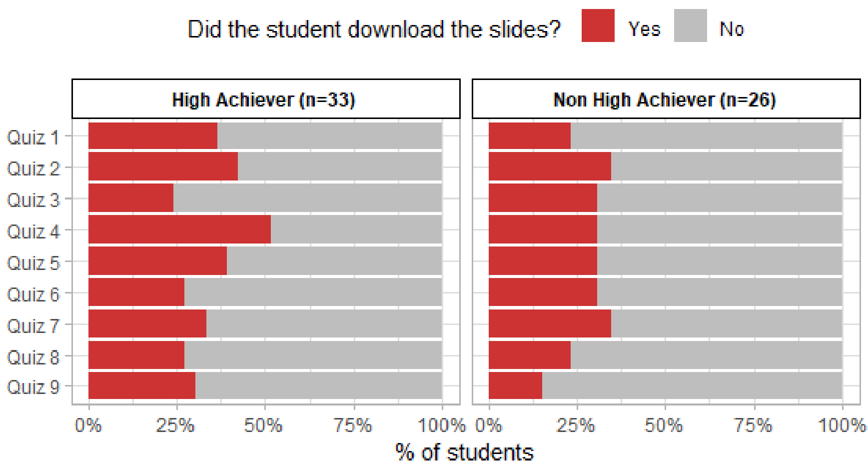


Figure 5.5: Percentage of students downloading each the slide deck at least once during the course.

dents' activity in learning platforms have been created to study the students' self-regulation behaviour. In this paper, considering the course's structure and assessment elements, the activity proceeding from solving a series of nine quizzes was used to analyse the usage of the learning materials. We address both the use of learning materials and how the students change their use over time, by analysing indicators created based on the students' time spent watching the videos corresponding to each quiz, their access to the slides provided, and the time they spent solving the quizzes. The data were gathered from two sources, (1) the LMS Canvas and (2) Echo360, a lecture capture platform widely used among undergraduate courses to stream lectures and facilitate lecture recordings and other educational materials. The reports from both data sources were merged, and the students' activity with the learning materials (videos and slides) was linked with the students' quiz submissions. To answer the research question *How do the high achievers use the educational material provided to get better grades?*, the students were classified as high achievers if their final grade in the course was at least 80 out of 100, and non high achievers otherwise.

Significant differences were found between groups. Firstly, high achievers not only got higher grades in both the course and the quizzes, they also spent significantly more time solving the quizzes compared with non high achievers. That difference could be explained by various causes, for example, the extent the students over-analysed their answers before submitting, or the extent they used external material such as notes, slides, or recordings while solving the quizzes. In our study, we found a positive relationship between the time the high achiever students spent solving the quizzes and their access to slides and lecture recordings. Regarding the access to lecture captures, high achievers showed higher levels of watching activity consistently throughout the course: (1) before starting the quiz, (2) while solving the quiz, and (3) once the quiz was submitted. Whereas similar results were obtained from analysing the slides viewing activity, no differences were found related to downloading the slides.

In addition, as the slides were provided through both platforms, the merged analysis allowed us to realise the platform preferences of high and non high achievers. Non high achievers, in contrast to high achievers, highly prefer to access the slides only through the LMS Canvas instead of Echo360. This may either be because they find more convenient the use of the LMS to access and interact with the slides, or because they were not used to or found the other platform more complicated or confusing. To address the latter, teachers using the learning platform in their courses to provide lecture recordings and other educational material should put more emphasis on providing the students with enough information about the learning platform to facilitate its adoption. Moreover, students would also benefit from consistency in the platforms used for teaching [14].

Our conclusions could be contrasted with research investigating other elements of learning related to engagement, and self-regulation behaviour in similar educational settings. Examples of such elements are lecture attendance records, discussion forum interactions, or activity in other educational platforms. In line with previous studies investigating varied ways of students' course participation and educational material use [98], our research shows high achievers' usage patterns were more consistent as the course progressed. In contrast, non high achievers show a work avoidance behaviour; which describes students who strive to maximise success through minimum effort [166]. Students that apply the work avoidance mindset to their studies, generally get lower grades [167], [168]. Our analysis also allowed us to examine how the high achievers usage of the learning materials changed. Those changes were primarily found in the ratio of lecture capture watched while solving the quizzes and after the quiz submission. The results of our analysis suggest high achievers learn to benefit from the course material available by heavily relying on the lecture captures to solve the quizzes and get higher grades. Despite the potential drawbacks of depending on the educational material provided to solve assignments, we consider this behaviour could be, under some circumstances, considered as beneficial for the students. Interacting with the course content while solving the quizzes, promotes that the students' to become familiar with the class syllabus, its content, and topics. Those interactions would increase the students' understanding of the class content, positively impacting their performance in other elements in the assessment structure, such as assignments, projects and exams.

Among the limitations of this study, in this course setting, the teacher allowed the students to take as much time as needed, and access the material while solving the quizzes intending to encourage them to make the most of the course content before the assignments and final project submissions. However, this course setting might prevent our findings from being generalised to other courses where the assessment structure does not allow such interactions with the learning material. Another limitation to this approach relates to the technical difficulty of merging the databases. Despite both platforms have relatively straightforward access to the data, the permits needed to download the reports, and their complex structure could make difficult for researchers and universities to extend their research on learning analytics to include more than one educational platform. Moreover, as the use of digital technology[1] to support teaching and learning processes increases, the amount of data available and the complexity to store, manage, and analyse the data also increase. These restraints advocate for implementing new methodologies and algorithms, closing the gap between learning analytics and information systems [135], [169].

Our results not only highlight the importance of considering all the educational platforms that are available to the students instead of limiting the analyses to the LMSs only, but also show the students select the platforms that better fit into their learning preferences. However, their selection might not be always the most suitable. Furthermore, it is recommended that the students receive guidance regarding the platforms they choose to rely on while studying. In order to better support the learners in regulating their learning processes, it is necessary to gain a deeper understanding of such self-regulated learning processes [102], [170]. Future work of this research relates to the replication of this analysis to other courses that use the educational platforms in similar ways. However, in this research, the approach is more important than the findings. This approach can be applied to different educational settings, courses from different fields, and taught using different teaching modalities.

In conclusion, integrating the two learning platforms was helpful to gain a better understanding of the differences between high and non high achievers regarding the use of lecture recordings and slides to get better grades. High achievers learn to make the most of both learning platforms and showed consistent engagement levels with the educational material as the course progressed. In contrast, non high achievers showed lower levels of engagement during the last two weeks and relied mostly on the LMS. Accordingly, our results point towards the value of extending the LA research on students' self-regulation by considering more than one data source. Such integration, as we have demon-

[1] Referred to as 'technology' in the published manuscript [2]

strated, provides relevant data to investigate the evolution of students' learning processes.

Chapter 6

A Learning Analytics Driven Intervention to Support Students' Learning Activity and Experiences

The rise of digital ecosystems in educational contexts brings both challenges and opportunities. The increased complexity calls for more dynamic digital competences, which can be challenging for teachers, but this complexity can also bring new possibilities in terms of data. Clickstream data, collected through each click in digital ecosystems, can be analysed and used to further our understanding of how students learn, which in turn can inspire changes in instructional practices. This chapter presents insights from a three-step action research case in an Icelandic University: i) a learning analytics approach is used to analyse how the students interact in the digital ecosystem; ii) the teaching structure was modified, in collaboration with the teachers to better match the way the students learn; and iii) the change in the students' experience and use of the digital ecosystem was evaluated. We argue for learning analytics as an important future pathway for advancing our understanding of how students learn and how teachers can adapt their teaching accordingly.

6.1 Introduction

Digital ecosystems, sometimes called educational platforms or virtual learning environments, have been on the rise in recent years. During the COVID-19 pandemic, closed schools not only forced an accelerated adoption of digital technologies to support distance and online education [135], but also favoured the adoption of external platforms to facilitate students' adaptation to new teaching modalities, such as virtual classrooms, lecture recording platforms, or online discussion forums [14], [171]. Adopting digital ecosystems, where all these technologies are combined to provide a holistic learning experience, brings both challenges and opportunities. While, the complexity of digital environments demands broader and more dynamic digital skills from teachers, this complexity also brings with it new possibilities for data analysis. The click-stream data, collected from every click on the services in the digital ecosystem, can be analysed and used to deepen our understanding of how students learn [32], [100], which in turn can inspire changes in teaching methods.

This chapter presents a Learning Analytics (LA) study. The study reported in this chapter has three phases: (1) the first, called Exploration, uses a data-driven LA approach to understand how higher education students interacted with the digital ecosystem before and during the pandemic, 2) the second, called Intervention, the teaching structure was changed as a consequence of the results obtained from the first phase. The class schedule and teaching modality were modified to better match the learning patterns of the students during the pandemic when they were able to choose the most convenient times and strategies for them. Finally, (3) the third phase, called Evaluation, analysed the effect of the intervention phase, addressing digital ecosystem's use and the students' perspective on the changes. More specifically, the exploration phase aims to answer the research question (RQ): *How did students change their patterns of study and their use of the digital ecosystem during the pandemic?* The evaluation phase, on the other hand, focuses on answering the RQ: *To what extent did the intervention support the students' learning activity?*

6.2 Learning analytics

LA is a growing multidisciplinary field aiming for understanding and optimising learning and its contexts to support educational practices [32], [135]. LA mainly bases on analysing learners' data from digital ecosystems' elements, such as Learning Management Systems (LMS) and other external platforms [97], [135]. Since its emergence, one of the key topics addressed by LA research has been the prediction of learners' academic performance [32], [42], [172]. To that end, measures created based on students' interaction data with digital ecosystems have been used as proxy to investigate and measure learning [32]. Nevertheless, this feature engineering process [173] is limited because indicators of activity frequency or interactions volume do not directly imply high quality learning [32]. However, digital ecosystems logs and activity data have been found to be a valid and useful proxy to measure behavioural aspects of student engagement, which are important predictors of academic success [100].

Behavioural aspects of engagement can be studied in varied ways, for example, the temporal evolution and consistency of interaction sequences [172] and usage of educational materials [2].

Generalisation of LA results must be taken with caution, because contextual variables of teaching, such as grading policies, differences between disciplines, and technology adoption have an effect on the results obtained through LA methodologies [45]. Consequently, it has been highlighted that beyond measuring learning itself, LA research is needed to better understand how students learn and engage with the learning resources to make teaching practices inclusive, flexible, and meet students' learning needs [97]. In that line, in the Nordic model of education the equity and equality of educational opportunities is enhanced [174]. To fulfil that goal, LA research should also be oriented towards the development of actionable recommendations to improve educational practices [42]. This chapter contributes to that call by illustrating how digital ecosystem data and LA research can motivate instructional changes.

6.3 Methods

6.3.1 Digital ecosystem overview

This study is based on data describing the students' activity within the elements of the digital ecosystem at an Icelandic University. From now on we will use the term 'interaction(s)' to refer to the activity within the digital ecosystem elements; for example, viewing pages, submitting assignments, or watching recordings, depending on the element the student is interacting with. The interactions also carry a timestamp. Depending on the needs of the courses and the preferences of the teachers, the LMS contains a variety of components that allow for the customisation of the course content. The common components shared by all courses are modules, assignments, and grades. Students use these three components to navigate the course structure and materials, access and submit assignments, and check their grades, respectively (Figure 6.1). The system also allows for the integration of external resources to support teaching and learning. One of them is Echo360, a lecture capture tool currently used to livestream and record lectures and provide students with access to recorded lectures and slides for many courses at an Icelandic University [14].

6.3.2 Analysis description

As described earlier, three phases were included: exploration, intervention, and evaluation. In the exploration phase, the learning patterns of students in five compulsory courses between 2019 (before the pandemic) and 2020 (during the pandemic) were analysed. This phase aimed to better understand students'

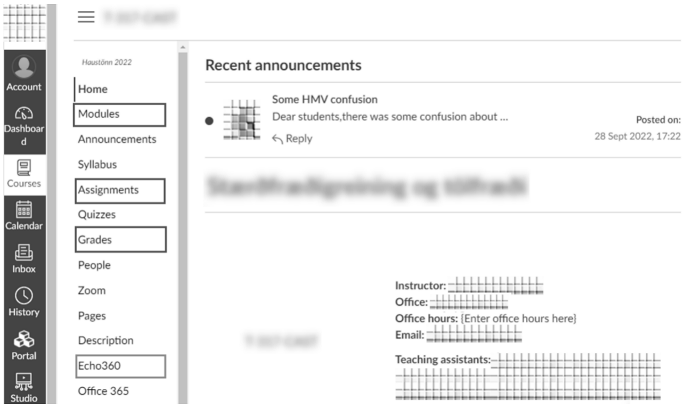


Figure 6.1: Digital ecosystem example: LMSs' common components (Modules, Assignments, and Grades) and external educational platforms (Echo360).

learning activity and how their activity changed when the pandemic hit and their education suddenly shifted to digital ecosystems.

The second phase, intervention, was built on the results of the exploration phase. These results showed that students' activity during the pandemic, when they had the freedom to study when they wanted, was more concentrated in shorter interaction windows. Figure 6.2 shows the phases timeline and describes the intervention in terms of sessions, modes of instruction, and students enrolled. The intervention was implemented with the intention of supporting the students by providing them with the flexibility to access the course content at times and in ways that were more convenient for them. Finally, the evaluation phase, with the aim of assessing the effectiveness of the intervention phase, focused on analysing the students' activities in course 1_A as shown in Table 6.1, between 2020 (during the pandemic) and 2021 (after the pandemic).

6.3.3 Data collection

This study analysed clickstream data from students' interactions with the digital ecosystem elements. LMS data were included in the exploration and evaluation phases to evaluate changes in students' access to course content and their learning patterns. Additionally, the evaluation phase included data from the external platform (Echo360) to examine how and when students viewed lecture recordings, and a series of semi-structured interviews with students to obtain student feedback on the intervention.

From the LMS, the clickstream contained the list of pages that students interacted with, including: timestamp, page URL, student system ID, and

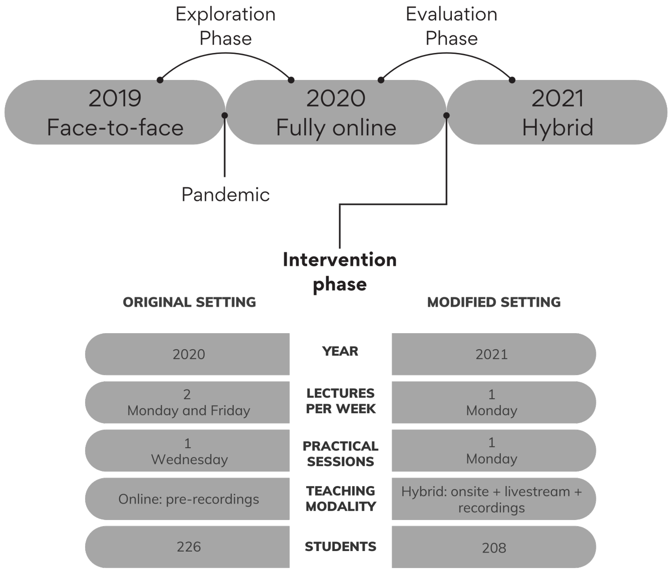


Figure 6.2: Phases' timeline and comparison between the original modified settings in the course 1_A.

Table 6.1: List of selected courses, year of study, and number of students enrolled each year.

Year of study	**ID**	**Course**	**2019**	**2020**	**2021**
First	1_A	Discrete mathematics I	225	226	208
First	1_B	Software requirements and design	319	284	Not included
Second	2_A	Calculus and statistics	131	159	
Second	2_B	Algorithms	207	250	
Third	3_A	Computer Networks	207	194	

course ID. From the timestamps, several interaction-related variables were created: part of day, part of week, and daily interaction window (Table 6.2). In addition, the final grades received by students (on a numerical scale of 0-100) were transformed into categories from A to D to facilitate analysis. Table 6.2 summarises these variables and their definitions.

From the external platform, each item in the clickstream corresponded to

30 seconds of video viewed and included information about the student's viewing activity, including: timestamp, student system ID, and lecture ID. In the semi-structured face-to-face interviews, which were conducted when pandemic restrictions allowed, students initially shared information about their backgrounds and workloads at school. The interview then evolved to reflect on how they attended lectures and practical sessions, used educational materials, and managed time.

Table 6.2: Definition of the variables created based on the LMS clickstream activity (i.e. students' interaction) and the students' final grade.

Variable		Definition
LMS component	Modules	Count of URLs containing "modules"
	Assignments	Count of URLs containing "assignments"
	Grades	Count of URLs containing "grades"
Part of the day	Morning	Usage ratio between 06:00 and 12:00
	Afternoon	Usage ratio between 12:00 and 19:00
	Evening	Usage ratio between 19:00 and 24:00
	Night	Usage ratio between 00:00 and 06:00
Part of the week	Weekdays	Usage ratio from Mondays to Fridays
	Weekends	Usage ratio from Saturdays to Sundays
Daily interaction window	LMS	Average daily difference in minutes between the first and the last interaction with the LMS
	Course-related	Average daily difference in minutes between the first and the last interaction with the content of a specific course
Grade category	A	Final grade >= 87.5
	B	Final grade >= 67.5
	C	Final grade >= 47.5
	D	Final grade <47.5 (Non-passing grade)

6.4 Results

6.4.1 Exploration phase findings

In this phase, analyses focused on evaluating statistical differences between student LMS usage before and during the pandemic. This section presents the main results of the analyses of the variables defined in Table 6.2. More course details, additional variables, and deep analyses and insights on the pandemic's effect can be found in previous work based on this data [129].

Due to the lack of normality and differences in the variances in the data distributions, the Kruskal-Wallis test was used to test for significant differences between years for the variables created. The p-values obtained in each test are shown in the graphs, with statistically significant values in bold. All tests were two-sided and the significance level for all tests was 0.05.

Changes on grades distribution (Figure 6.3):

Statistically significant differences were found in three of the five courses included in this phase, the second- and third-year courses. In these courses, in addition to the change in teaching modality brought about by the pandemic restrictions, the assessment structure and teachers' grading policy were also changed, affecting the distribution of grades between years [45]. Conversely, courses without significant differences in grade distribution were 1_A and 1_B, both first-year courses, where only the teaching modality changed.

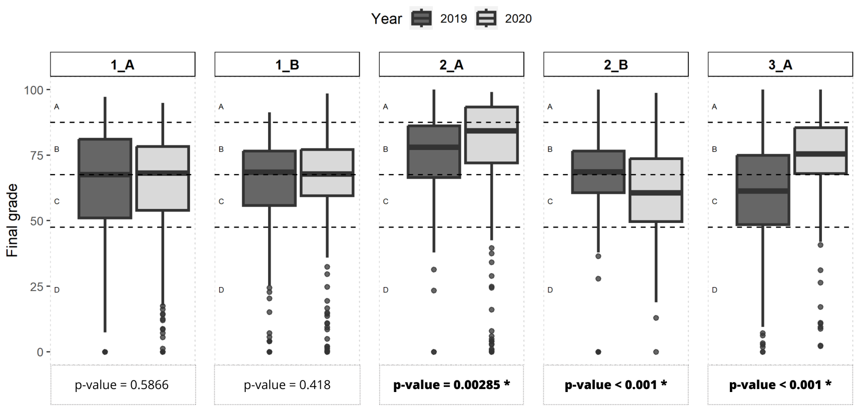


Figure 6.3: Comparison of final grades distribution. Dotted lines indicate the A, B, C, and D grade categories defined in Table 6.2.

Changes on LMS usage (Figure 6.4):

Although interaction with digital ecosystems is not a direct measure of learning, clickstream data in these systems can be seen as a proxy for what elements the students focus on when studying, and how they distribute their time [100]. To understand how students' activity changed during the pandemic, we looked for significant differences at the level of interaction with the LMS components. Unlike the Modules and Grades components, where changes in interaction levels were not consistent across groups, the five groups showed statistically significant differences in interaction levels with the Assignments component[1], indicating that students' interaction levels with this component

[1]During the pandemic, Course 3_A had more assignments. All other courses remained unchanged [129].

changed during the pandemic.

Changes on the time distribution during day (Figure 6.5) and week (Figure 6.6):

To analyse how students distributed their study time, the following analyses focus on evaluating significant differences in usage ratios at different times of day and week. In the following tests and graphs, usage ratio represents the proportion of all interactions at the given time. Regarding the time distribution during the day, there was a decrease in the proportion of morning interactions in all courses during the pandemic. While all courses had an increase in usage during the afternoon or evening, only one course had significant changes during the night. For distribution during the week, significant differences were found in all courses for the interaction between weekdays and weekends. In four courses, the proportion decreased on weekdays and increased on weekends.

Changes on the daily interaction window (Figure 6.7):

This analysis focused on the changes in the daily interaction window with the LMS and course content. Our analysis showed that the time spent interacting with both the LMS and course content decreased for all courses during the pandemic. We performed a proportion test using the median minutes per group to assess the extent to which the percentage of decrease differed between the LMS and the course content. Proportions and p-values in Table 6.3 show that the decrease in the interaction window with course content was higher for all groups, suggesting the activity was concentrated over shorter periods.

Table 6.3: Proportion test computed over the median on each course and year.

Course	LMS (2020 vs 2019)	Course content (2020 vs 2019)	X-squared, p-value
1_A	86%	62%	66.856, **<0.001 ***
1_B	89%	62%	93.445, **<0.001 ***
2_A	87%	77%	11.89, **0.0005643 ***
2_B	92%	85%	8.9552, **0.002767 ***
3_A	93%	71%	82.989, **<0.001 ***

6.4.2 The intervention phase

The results of the exploration phase can be summarised as follows: students' interaction levels changed and their study sessions were more intense, because

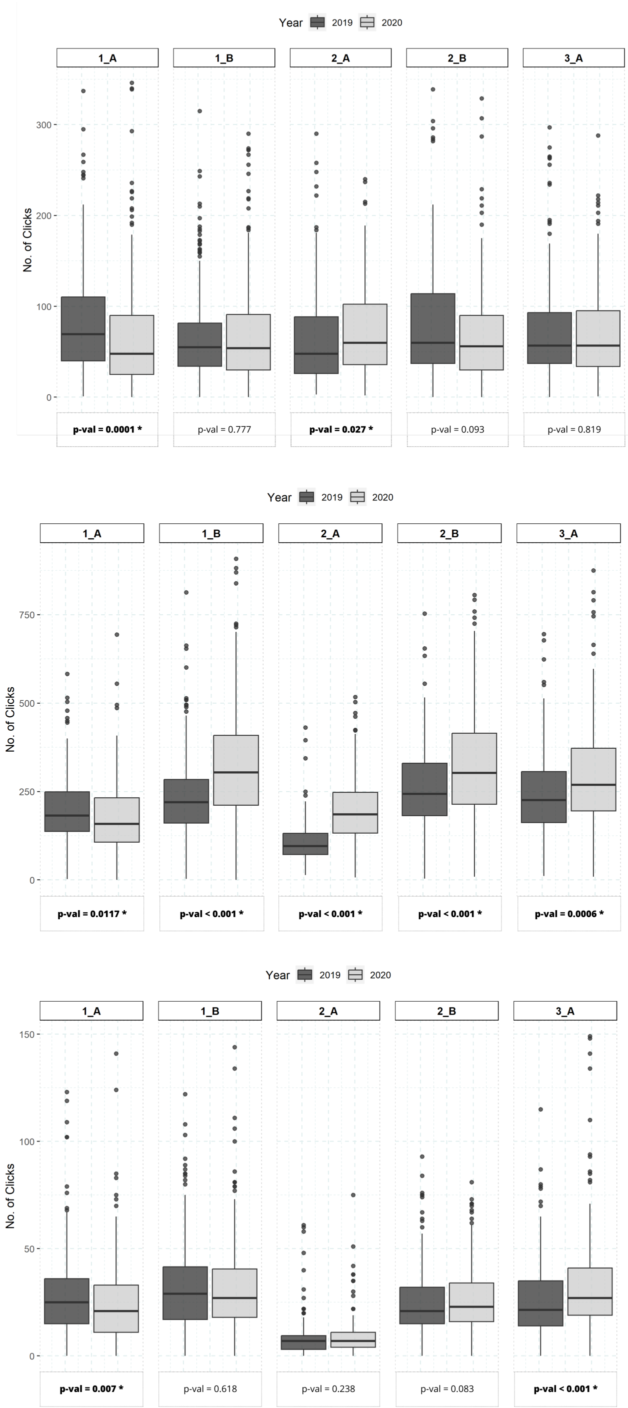


Figure 6.4: Interaction level during 2019 and 2020 for components Modules (top), Assignments (center), and Grades (bottom) split by course.

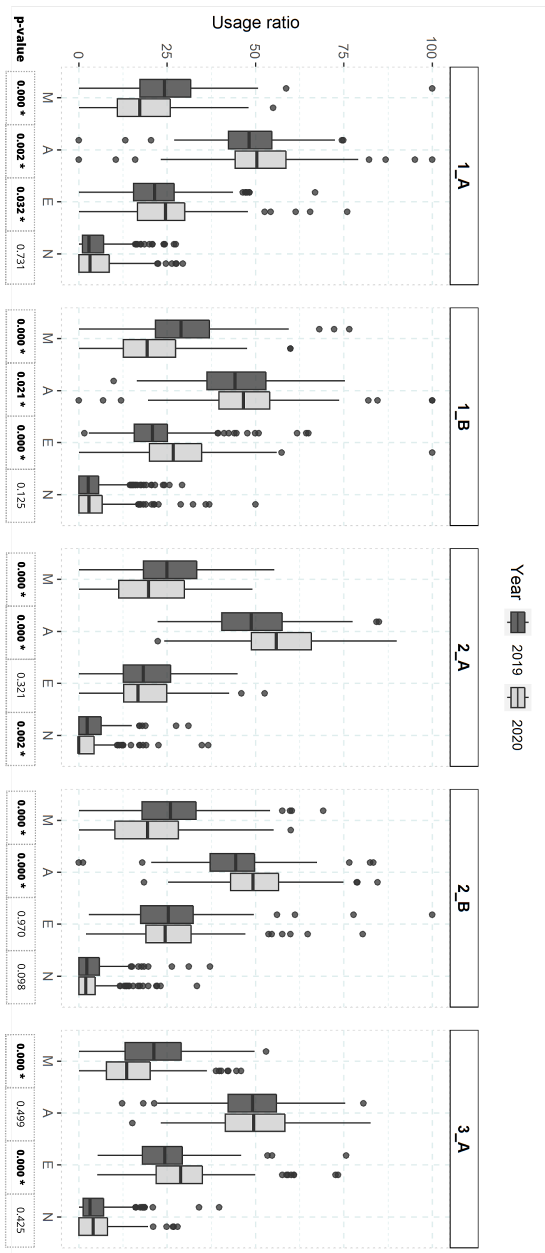


Figure 6.5: Usage ratio at Mornings (M), Afternoons (A), Evenings (E), and Nights (N) as defined in Table 6.2.

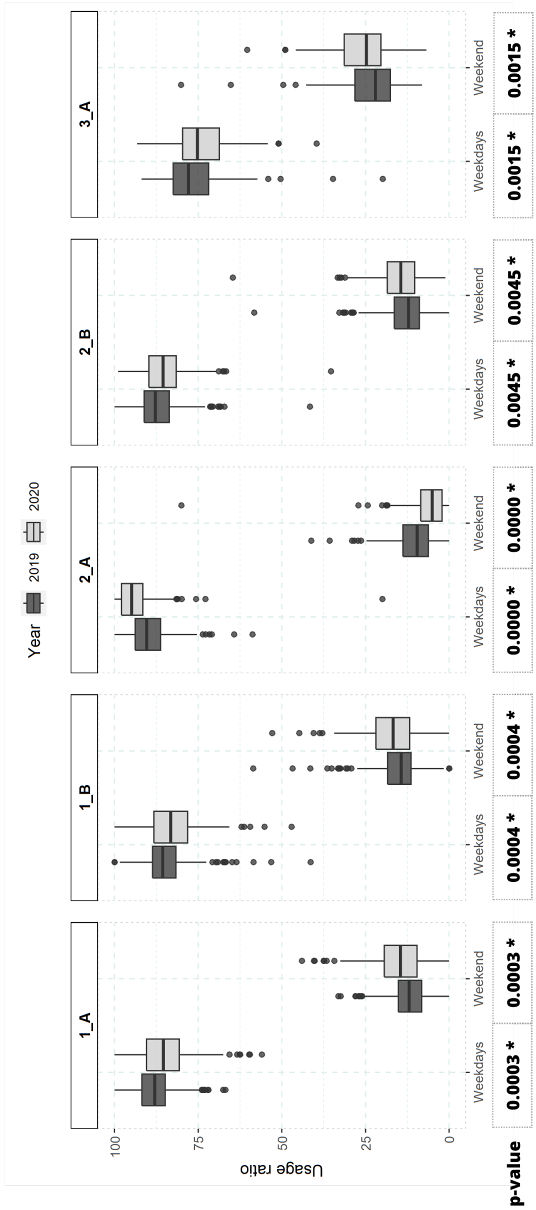


Figure 6.6: Usage ratio during Weekdays and Weekend as defined in Table 6.2.

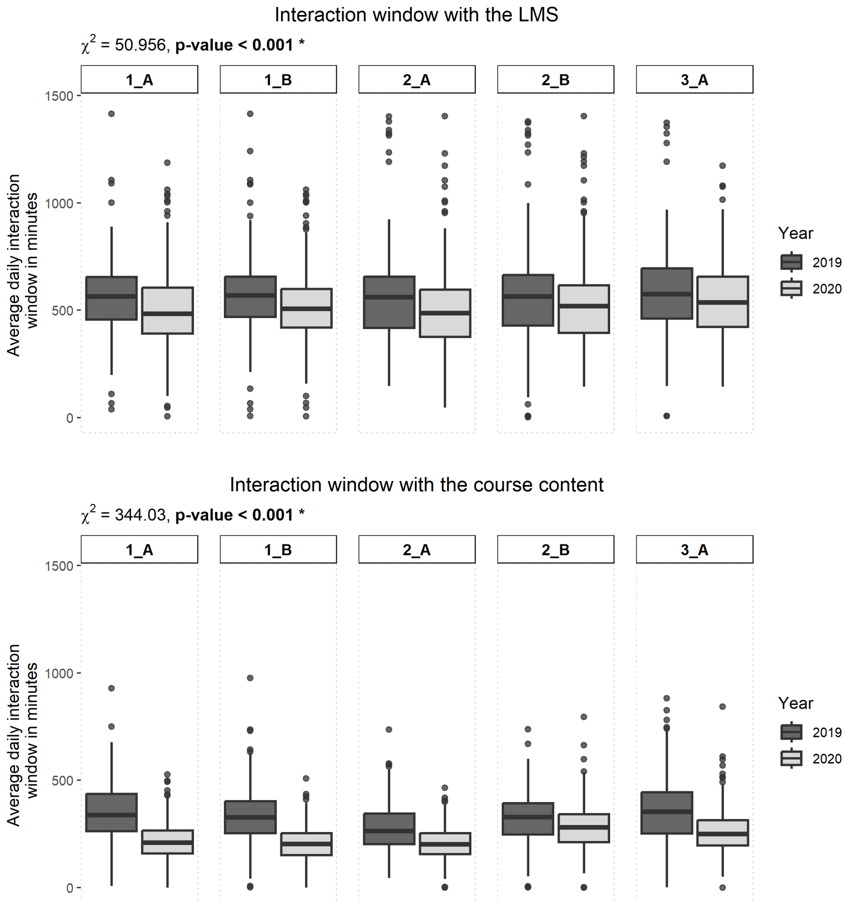


Figure 6.7: Average daily interaction window with the LMS (top) and the course content (bottom).

interaction with course content was concentrated in smaller interaction windows during the day. A change in the schedule to better accommodate students' new time management and study patterns was inspired by the identification of this new way of organisation. The intervention (Figure 6.2) was implemented in course 1_A and the students were informed during the first lecture about the change in the schedule compared to previous years.

In addition to the schedule change, another important change from 2020 to 2021 was the teaching modality. In 2020, due to the pandemic restrictions that were still in place on university premises, teaching was delivered entirely online through the digital ecosystem. By 2021, some of these constraints were relaxed, allowing teachers and students to decide whether to attend classes face-to-face or online. For course 1_A, the teaching modality changed to hybrid in 2021, the students could attend in person or join the livestream (Figure 6.8). In addition, class lectures were recorded and uploaded to Echo360. The practical sessions were not recorded.

Figure 6.8: Hybrid teaching class set up.

6.4.3 Evaluation phase findings

This subsection presents the results of the analyses conducted to evaluate the effect of the intervention on grades, interaction windows, and viewing of lecture recordings in course 1_A between 2020 and 2021. Intervention effects according to students' interviews are also presented.

Intervention effect over grades distribution (Figure 6.9):

No statistical evidence of differences in grade distribution between years was found. That is, in line with the results of the previous phase, the new schedule and teaching modality did not have a negative effect on the students' grade distribution.

Intervention effect over the daily interaction window (Figure 6.10):

As mentioned above, the intervention aimed to support the students' new time management strategy by facilitating shorter interaction windows. To assess

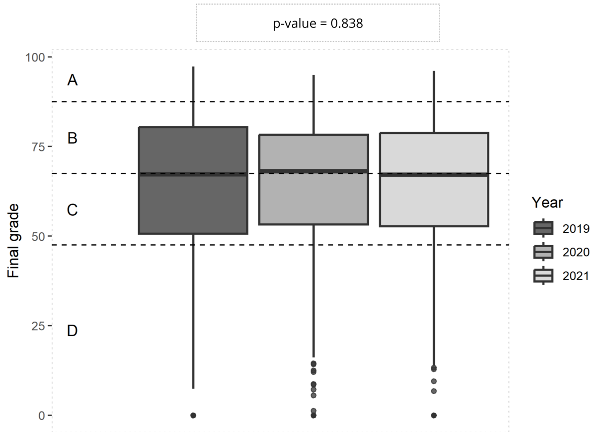


Figure 6.9: Final grade distribution comparison from 2019 to 2021 in course 1_A.

how successful the intervention was in this regard, we tested for differences in average daily interaction windows with the LMS and course content. As no significant differences were found, the results were an indication that students had similar interaction windows when the intervention was in place.

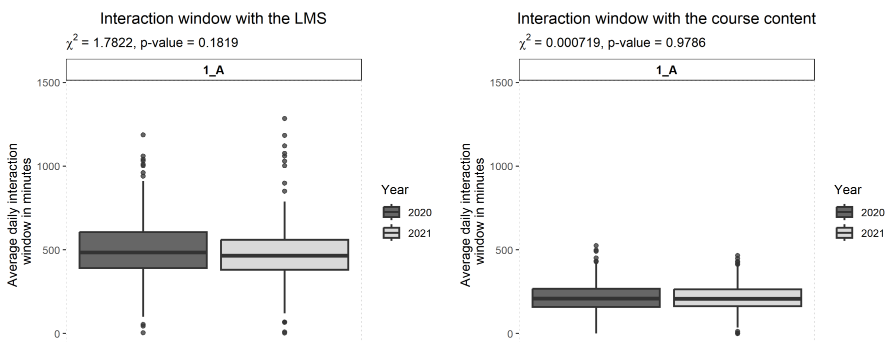


Figure 6.10: Comparison of the average daily interaction window with the LMS (left) and the course content (right) between 2020 and 2021.

Intervention effect over the lecture recording viewing:

Since the activity and interaction window with the LMS and the course content remained the same after the intervention, examining the activity within the external platform over the semester allowed us to understand how students adapted to the new teaching setting. This analysis focuses on the differences in students' use of lecture recordings between 2020 and 2021. In this regard, despite the difference in the number of lectures per week, the total length of the videos during the semester was similar: 1,924 minutes in 2020 and 1,919 minutes in 2021. For analysis, videos were grouped based on the week they were published.

For the first analysis, for each video published to Echo360, we calculated the ratio of video watched by comparing the number of minutes watched by each student to the video length. The ratio, a score greater than or equal to zero, can be interpreted as the percentage of the video viewed. A score below one indicates partial viewing, while a score above one indicates repeated viewing. Figure 6.11 shows how watched ratios changed based on the week the videos were released. In 2020, since the teaching modality was fully online, students had to watch the recordings completely in order to access the class content. Therefore, the range of the ratios watched was centred around the value one. In contrast, in 2021, with the hybrid teaching modality, watching lecture recordings was not mandatory as students could attend lectures in person and access recordings only when needed, making the range wider.

The differences in the number of outliers could also be the result of changes in the intervention. In 2020, as the practical sessions were held in a different day and through online sessions, more students watched the recordings several times, as indicated by the outliers in the distributions for each week. In contrast, in 2021 as the practical session was held on the same day, the number of outliers was reduced because the students did not have to seek the course content or they could directly ask the teaching assistants during the practical sessions.

The watching ratios shown in Figure 6.11 were split by grade category as defined in Table 6.2. The split, shown in Figure 6.12, helps to identify the differences in the consistency of watching activity over the course among students in different grade categories. From this split, several highlights emerge: (1) The differences between grade categories are less pronounced for 2021 than for 2020. In 2020, the D category, compared with other categories, watched a smaller percentage of the lecture recordings published, and their activity was less consistent during the term. For 2021, similar conclusions are reached, but the differences between the categories are subtler, specially between C and D categories. (2) In both years, outliers showed that among students who viewed recordings multiple times along the course, most were in category B. (3) In

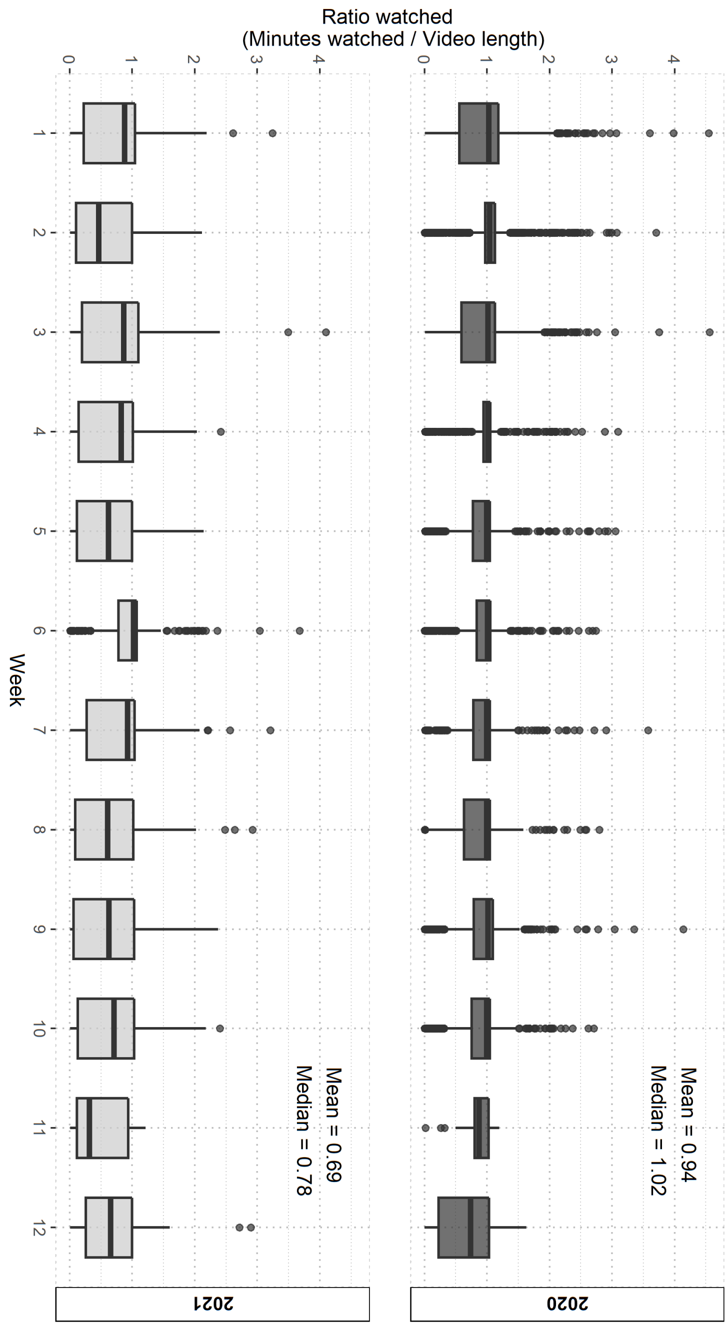


Figure 6.11: Comparison of ratio watched by 1_A students between 2020 (top) and 2021(bottom).

2020, in contrast to 2021, the C students also demonstrated higher levels of watching activity and interaction with the lecture recordings, suggesting that the recordings were yet an essential resource for them.

The second analysis focused on when students watched the lecture recordings. To this end, we compared the week in which the recording was published with the week in which the student watched the recording. Figure 6.13 shows the comparison between publication (y-axis) and watching (x-axis) weeks. Beyond the presence of outliers indicating students watched the recordings several weeks after they became available, the time when students watched the recordings differed by teaching modality. In 2020, with fully online teaching, most students watched the recordings within a week after they were published. In contrast, in 2021 with hybrid modality, students took longer to view the recordings, from three to six weeks in some cases. No differences were found in the watching week when split by grade category.

Students' semi-structured interviews:

Content analysis of the interview transcripts was performed following a process coding method [175]. Students' contributions were categorised into positive and negative elements. In terms of positive elements, the students shared the lecture recordings and the new schedule facilitated their learning process and assignment submission. Most of them would also choose online attendance and similar schedules with all sessions on the same day. Furthermore, they liked the attendance flexibility offered by the hybrid modality, and agreed on the benefits of having access to lecture recordings. On the other hand, the negative elements identified by the students were related to the mix of teaching modalities offered in different courses during the term, missing information due to technical issues, or lack of experience with external platforms. Students also mentioned the new class schedule could be taxing when implemented for more difficult courses, where having time between sessions would allow them to better assimilate the course content. In addition, the students expressed that they would like to have the option to provide feedback and receive guidance on how to use the platforms and access the course content.

6.5 Discussion

This study is presented in three phases; exploration, intervention, and evaluation. The exploration phase' results provided insights into the changes in the study patterns followed by the students when the pandemic forced the transition to digital ecosystems. These results pointed towards changes in the way the students organised their study time during the day and week, and changes in the interaction with the course content, showing the students' activity was more

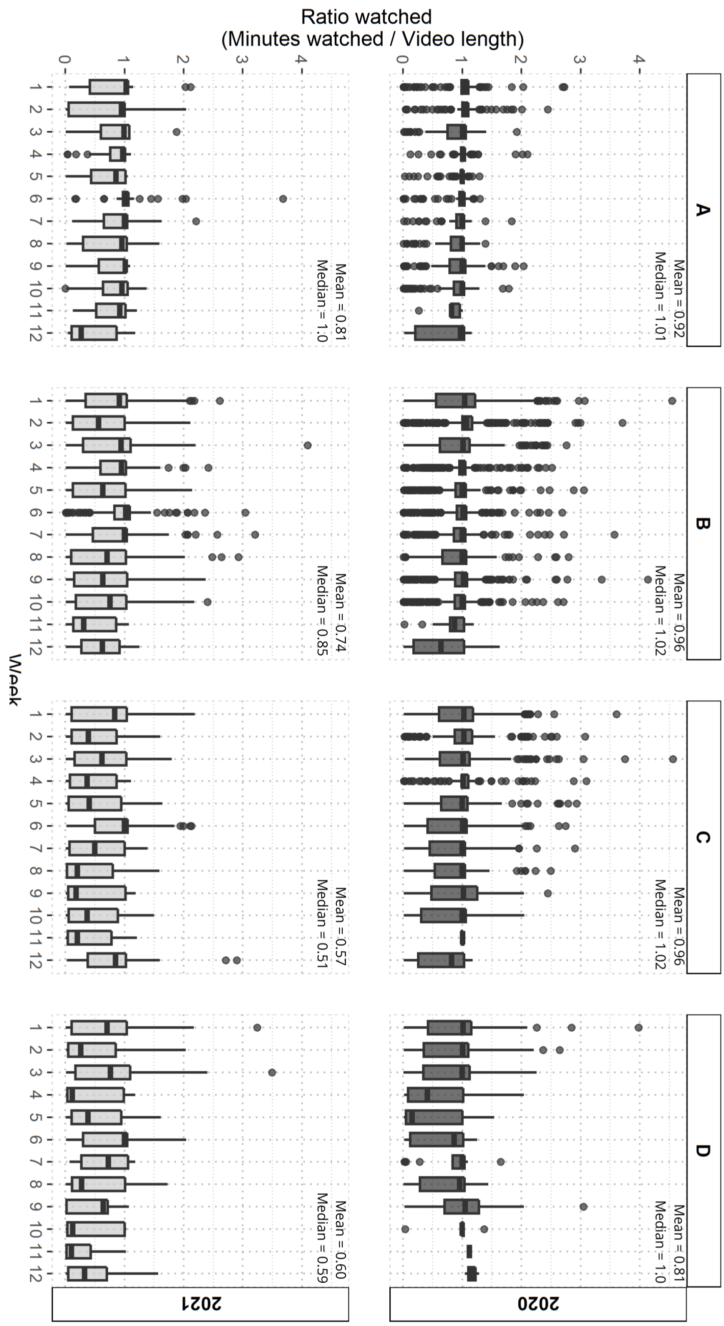


Figure 6.12: Recordings ratio watched split by grade category during 2020 (top) and 2021 (bottom).

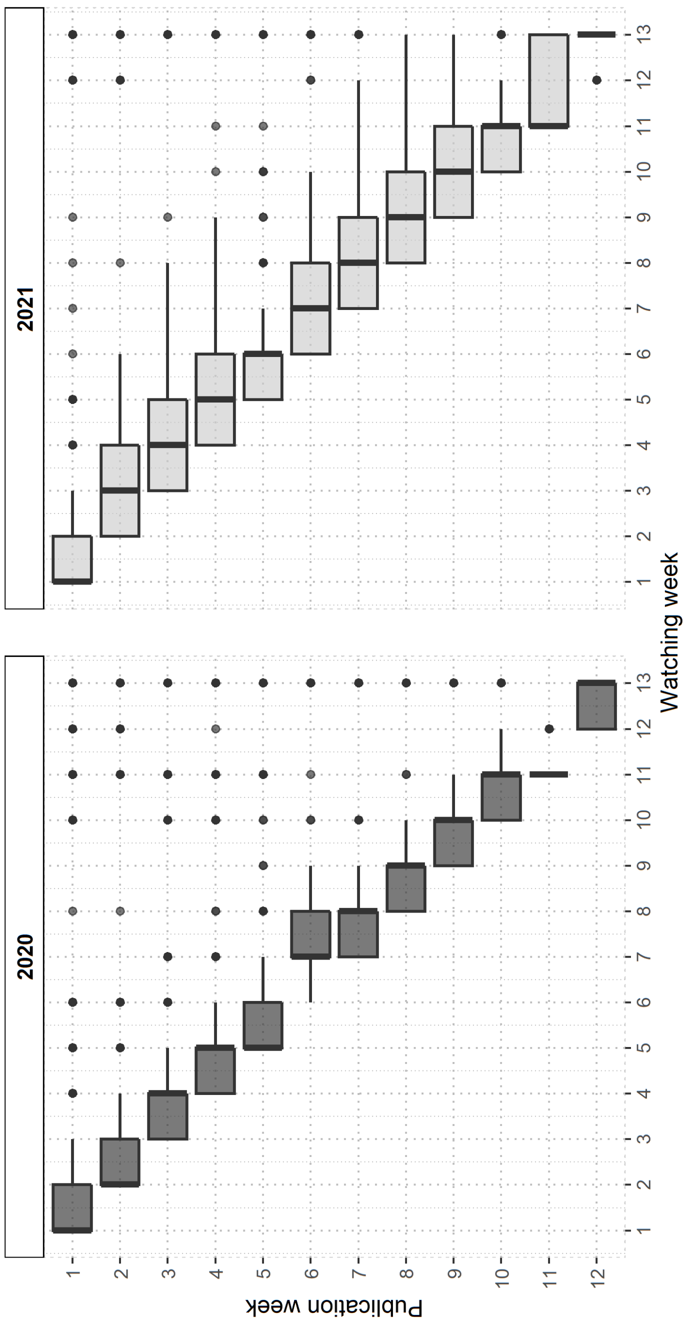


Figure 6.13: Comparison between publication week and watching week for 2020 (left) and 2021 (right).

intense and focused, as the interaction with the courses' content was highly concentrated in smaller interaction windows during the day. The identification of this new way of time organisation was key to propose the changes in the intervention phase to better accommodate the students' new time management strategy. The analysis performed in the evaluation phase provided insights into the effect of the intervention over learning patterns, lecture recordings usage, and final grades. The evaluation phase showed that interaction patterns with the LMS did not change, but the use of lecture recordings did. Moreover, this phase revealed the intervention did not impact negatively nor positively the grade distribution.

One of the main contributions of this study relates to the implications of the lack of difference in the distribution of grades between years. First, this study compares three first-year courses with similar content, group size, assessment structure, and intended learning outcomes, but with different teaching modalities: face-to-face (2019), fully online (2020), and hybrid (2021). From this perspective, since it had no effect on the grade distribution between years, it could be argued that there is no relationship between the teaching modality and the achievement of learning outcomes. On the other hand, despite similarities between courses, as the LA research still faces limitations to generalise results to different educational settings [42]; the academic performance between different students' cohorts may not be directly comparable. However, previous research focused on the effects of sudden teaching methods' changes on learning outcomes and time management skills has found that students in their first year of study have stronger self-regulation skills than might be expected [176]. These results combined suggest that first-year students demonstrate adaptability when exposed to different teaching modalities.

Another contribution, relates to class scheduling research. In the past, research has focused on determining the optimal class length and number of sessions per week based on various data sources, such as surveys, final grades, and assignment performance [177], [178]. Moreover, class schedules are established based on various factors, such as academic credits, professors' timetables, room availability, course size and the required technology. In our work we show that digital ecosystem usage and learning patterns are insightful elements for designing class schedules that better fit the students' learning patterns. In the past, similar changes in class schedules have been found to be beneficial for efficiency and flexibility [179], we show the change positively aligned with the learning patterns and did not affect the grade distribution. However, as the students reflected, it could be exhausting for complex courses.

A final contribution relates to the lecture recordings provided. Lecture recordings have been found to be particularly beneficial for first-year students, helping them to overcome language barriers and facilitating their adaptation to university teaching methods [113]. In line with previous research [2], [171], we show lecture recordings are a valuable resource that not only supports learning processes, facilitates the students' access to the course content and provides flexibility, but can also help to identify changes in learning activity over time.

To summarise, in this chapter, we presented a LA example of how universities can extract value from digital ecosystems data and use it to inspire changes according to students' needs: the successful implementation of an intervention on class schedules and teaching modalities. Our analysis showed that providing learning materials in varied and convenient ways facilitated students' access to course content, the hybrid modality favoured students with different needs by allowing flexible class participation, and students expressed that the new schedule and teaching modality were beneficial for focusing and engaging with the course content. This chapter not only demonstrates that digital ecosystems are valuable data sources for understanding how changes in educational provision affect students' learning experiences and academic performance, but also that is essential to analyse how students interact with multiple elements in the digital ecosystem to better understand how they learn. This knowledge can inform strategies to improve teaching and learning practices.

Although the results of this analysis cannot be generalised to other settings, we urge the reader to follow the methodology presented and leverage the positive impact that LA research could have on educational environments. Future research includes performing similar analyses on courses from different departments, interactions with other elements of the digital ecosystem, and identifying courses that would benefit more from this type of modification.

Chapter 7

Supporting Teachers in Higher Education: Design of an Institutional Programme from a Socio-technical Perspective

The acceleration of digital technology adoption in higher education, prompted by the global shift to online teaching during the COVID-19 pandemic, called for responsive programs to address pedagogical challenges. This paper presents a university-wide programme designed to support instructors in providing educational resources for online and hybrid undergraduate courses in a Nordic University. By adopting a socio-technical perspective, the programme encompasses teacher support and digital platform use. Additionally, the program aimed to enhance student experience by increasing course consistency and facilitating data collection for future research on learning analytics. Our findings demonstrate the programmes' successful adoption, effectively strengthening instructors' practices. Key contributions include an instructor-centric perspective on digital technology challenges and a socio-technical conceptualisation informed by educators' experiences during the pandemic. This research provides valuable insights for educators, administrators, and researchers developing similar initiatives for effective faculty professional development in online and hybrid teaching environments.

7.1 Introduction

Due to the COVID-19 pandemic, the educational provision has adapted to major changes and accelerated digital technology adoption. The number of digital platforms used for teaching has increased, and their usage has changed [109], [180]. Since the first term of 2020, most institutions changed from on-site teaching, to distance learning conducted online [130], [181] to follow the restrictions imposed by the governments [49]. Several communication channels such as digital platforms that offer streaming and conferencing features, and Learning Management Systems were the protagonists of the online lectures and virtual classrooms in the so-called Emergency Remote Teaching (ERT) [50], [51]. Following this state, high inconsistency in the digital platforms used to support teaching provision across undergraduate courses has been observed since the COVID-19 pandemic started spreading in late 2019.

The ERT period was challenging for students and instructors alike, significantly impacting the way the education was provided. Most teaching practices changed from an on-site only practice to distance and online teaching practices with a mix of synchronous and asynchronous modalities [182], which included online flipped classrooms, pre-recordings, and streamed lectures which supported the emergency teaching modality since the first months of the pandemic [109], [130], [183]. Studies have been conducted on the effect and impact of the ERT on teaching and learning in varied educational settings. For instance, changes in students' learning patterns, motivation and engagement levels have been studied [180], [183]; as well as the pre-pandemic students' study profiles and their relationship with the forced change in the teaching modality to online and distance learning [1].

There were multiple challenges instructors faced during this period, including feelings of ineffectiveness when it came to using digital technology [184], [185], the lack of institutional support for professional development [186], and the need for pedagogical and technological training [187]. Although instructor readiness for virtual environments improves with the provision of organisational support [188], the need for evaluating how digital technology is used [185] and developing teaching models to support instructors in blended educational settings after the pandemic remains [189]. Moreover, regardless of the rapid digital technology adoption experienced, leading educational digital transformation effectively requires digital competence [190], emphasising the importance of providing adequate training and support for instructors.

In this paper, we describe the design and adoption of an institutional programme launched during the pandemic at Reykjavik University. The programme had the objective of providing guidance and support for creating and providing educational material in undergraduate programmes during and after the pandemic. For its design and adoption, we followed a socio-technical perspective of learning [104]. In educational settings, the socio-technical perspective involves human and technological participation, along with learning (internalisation and cultivation of knowledge) as a process, and learning management systems as resources [107]. We use a qualitative approach. Thirteen semi-structured interviews were conducted, transcribed, coded, and analysed through content analysis [191]. The insights obtained were used as a guideline to create and improve the resources included in the programme. We discuss the challenges and practical implications of the initial programme adoption, as well as its implications for research.

The structure of the paper is as follows. Section 7.2 introduces relevant literature in relation to the implications of the use of digital platforms during the pandemic and socio-technical arrangements. Section 7.3 outlines the methodology, including the social and technical elements that were incorporated and the programme objectives and structure. Results are presented in Section 7.4, including the semi-structured analysis findings, and the initial adoption of the programme. Implications, limitations, and future work are presented in Section 7.5. Finally, Section 7.6 presents the conclusion and main contributions of our work.

7.2 Related work

7.2.1 Learning platform usage during and after the pandemic

Platforms do not cause learning. Rather, it is how they are used and how the resources within them are accessed and used that determines whether learning takes place. In recent years, along with the increased facility of accessing online resources, the availability of online programmes has also increased [192]. As a matter of fact, since the beginning of the COVID-19 pandemic, a marked increase has been observed in the use of digital educational platforms for supporting the delivery of education [109], [180]. Nonetheless, despite their rapid and, in many cases, forced adoption, there is still a growing need for investigating the digital learning platforms' features that are mostly needed by teachers and students for different teaching modalities [107]. The most challenging aspect of this goal is that even though online learning and its features have been widely investigated and were fully adopted by most institutions during the pandemic, the post-pandemic landscape of higher education has also changed significantly as the emergency setting could not be considered a suitable long-term solution [156].

The pandemic and the ERT adopted to guarantee the access to and continuity of educational programmes had multiple effects on stakeholders and resources, including faculty, students, institutional leaders, course materials, teaching strategies, classroom technology, and instructional design [156]. Despite the fact that students and teachers are back in the classroom, the use of digital tools and platforms is shaped by either positive or negative experiences [152]. For example, Lewis, Deng, Krause-Levy, *et al.* [193] investigated students' experience with remote teaching during the pandemic. In their studies, both the use of lecture recordings and asynchronous assessments had a positive effect on enhancing the students' remote learning experience; however, the negative effect was the decreased sense of connection between the students and their peers due to the remote setting. Code, Ralph, and Forde [157] focused on the teachers' concerns and perspectives for post-pandemic education. In their study, teachers' concerns were found in relation to five main topics: curriculum, equity, motivation and engagement, effectiveness, and sustainability.

Teachers' challenges mentioned in the literature are related to the lack of guidance and training on distance learning modalities, work overload, lack of interaction with the students, and difficulty in upholding students' motivation levels [153]. In addition, regarding the ERT and its perceived benefits as well as positive effects on education, increased flexibility, and successful digital technology adoption have been emphasised. Students and teachers have communicated their satisfaction about the experience with online and distance learning, the on-demand access to digital learning material, and the flexibility in the distance teaching modality [130], [153]. The first insights about the future of education in the post-pandemic era indicated that those elements, as well as online, blended, and hybrid learning, were more likely to remain present in higher education [156]. Furthermore, a higher number of online courses gives the students the possibility to choose whether they would prefer to attend the lectures on-site or online [157]. In consequence, higher education institutions must identify the digital platforms that best accommodate their strategies for online and hybrid teaching and learning provision [156].

7.2.2 Socio-technical arrangements and digital platforms

The existing research on digital platforms and ecosystems, hereinafter called 'digital platforms', often puts weight on the technical aspects of these systems without considering their social context, which is essential for understanding the digital platform dynamics [103]. In contrast, research undertaken from a socio-technical perspective accounts for the interactions between two components or subsystems, without utilising either the social element or the technical element as the focal point. These interactions have been conceptualised in a socio-technical system defined as the "Recognition of a recursive (not simultaneous) shaping of abstract social constructs and a technical infrastructure that includes technology's materiality and people's localised responses to it" [56, p.42]. Although the definition of socio-technical systems has evolved, the underlying concept remains the same, recognising the importance of both the technical and the social subsystems [57]. The technical subsystem includes the physical infrastructure (hardware), software, and the associated platform mechanisms [57]. The social subsystem, on the other hand, is composed of individuals, relationships, and human attributes [57]. An integrated socio-technical perspective attempts to understand subsystem interactions, optimise their fit or harmony, and improve platform (instrumental) or social (humanistic) outcomes [57]. Furthermore, as socio-technical systems scale, new capabilities, and novel services are created, leading to the emergence of new socio-technical arrangements, Kapoor et al. [103] also suggested more research is needed on the organisational aspects of platform ecosystems, to investigate social challenges, and the dynamics of participants in the social subsystem.

Bednar and Welch [104] emphasise the socio-technical nature of learning. They describe learning as efforts to leverage internal and external procedures, and note its evolutionary characteristics. Nonetheless, although the socio-technical perspective emphasises the importance of interactions between the subsystems, the whole system can be characterised by four elements, namely, people (or actors), technology, task (or process), and structure (or communication tools or resources) [105]–[107]. In educational contexts, these elements correspond to instructors and students, the digital platforms used for teaching, the knowledge or skills being communicated, and the environment, respectively [108]. These elements and their characteristics, including users backgrounds, technology fit to the task requirement, as well as task and system attributes, influence the adoption of digital educational platforms, including learning management systems and their integrated elements [106]. In regards to digital learning platforms, socio-technical approaches have been adopted in digital workplaces to support professional development programmes along with participatory action research [194]. A number of other case studies can be found in the assessment of e-learning platforms during the pandemic [195], as well as an investigation of how curriculum development is being developed in vocational education through the implementation of digital technologies [196].

Furthermore, this perspective has been found to be adequate to investigate the use of digital technology in higher education in varied contexts and from both students' and instructors' perspectives. For example, on the students' side, Fair [197] adopted a socio-technical perspective for higher education module design, reviewing theoretical and pedagogical underpinnings in an undergraduate course, recognising the importance of pedagogy and learning theories as well as the students' needs and digital literacy. On the other hand, Islind, Norström, Vallo Hult, *et al.* [107] investigated the teachers' perspective on how the students engage in learning, focusing on the shift between classroom and digital platform interactions, showing how such interactions enhance learning. Wang, Solan, and Ghods [105] proposed a socio-technical-based model for evaluating success in higher education distance learning. Moskal, Stein, and Golding [198] also adopted an instructors' perspective to assess the engagement levels with evaluation systems, positively influencing it by addressing technical limitations. Finally, in a comparable study, Olney, Walker, Wood, *et al.* [108] investigated faculty adoption practices for dashboards created based on

Learning Analytics (LA) methods.

Even though it has been shown that digital platform engagement is improved when technical limitations are addressed properly [198], providing access to learning resources alone does not guarantee that learning will occur effectively [106]. That is, learning will be unlikely to occur by purely providing technological resources and expecting users to equally benefit from them. In contrast, stakeholders in learning environments are active digital technology recipients, whose use of technological tools and resources adapts in multiple ways depending on their contexts [108]. Therefore, in order to drive effective digital platform usage and learning, both social and technical components should be integrated [199]. In this work, we adopt the ontology of the socio-technical perspective for evaluating potential uses of a digital educational platform in the transforming period during and after the pandemic, supporting instructional material design, and assessing the instructors' adoption of the digital platform. We argue that the integration of both subsystems will benefit from gaining a better understanding of how stakeholders' (instructors') needs can be fulfilled by digital technology's (digital educational platform's) features.

7.3 Methodology

In this section, we present the social and technical elements that formed the basis for the institutional programme created in this research. On the social side, the instructors' experience with digital educational platforms during the pandemic was investigated, leading to the identification of the technological features needed to support instructors in creating and providing educational material to undergraduate students. The technical side focuses on a digital educational platform already in use to some extent at Reykjavik University.

7.3.1 The social subsystem: Instructors experience during the pandemic

Two rounds of interviews were conducted. The first one, from now on called *design phase*, started in early 2021, still under pandemic restrictions. Six professors of undergraduate courses at the Department of Computer Science at Reykjavik University were interviewed. Four participants were female, two were male, and the age ranged from (34-60). The semi-structured interviews evolved around the transition to fully online teaching imposed by the pandemic, including the digital learning platforms used, changes in teaching methods, assessment structures, as well as challenges faced by the professors in that period. The second round of semi-structured interviews, referred to as *application phase*, had place in August 2021, before the start of the autumn term.

In this round, we interviewed seven professors who were invited to take part in the institutional programme created (See Section 7.3.3). Five of the professors participating were female, two were male, and the age ranged from (34-60). Each professor belonged to a different department at the University.

In total, our data consists of 13 interviews. The interviews were recorded and transcribed verbatim. In this study, we use a qualitative approach, the interviews' transcriptions were organised, categorised, coded and analysed through content analysis [191]. In the design phase, the analysis focused on understanding the instructors' experiences related to technological challenges and features adopted in response to pandemic restrictions. The findings, which served as the basis for creating the initial version of an online repository of tutorials, are presented in Subsection 7.4.1. On the other hand, for the application phase, the analysis sought to identify specific requirements the participants had for the courses they would be teaching during the next term (Autumn 2021), their previous experience using the digital platform, as well as specific concerns in regards to the digital platform functionalities. The findings, used as a guideline to provide the participants with tailored recommendations and tutorials, are presented in Subsections 7.4.2 and 7.4.3.

7.3.2 The technical subsystem: The digital platform

The digital educational platform selected for the programme is Echo360 [164]. Among its features, the digital platform facilitates live-streaming, video pre-recording, and delivery of lectures and educational material to the students. It offers a set of engagement tools to help the teachers enhance the lecture provision, and improve the students' participation and engagement with the lecture content. In addition, it also includes tools available for students to use during or after the lectures for studying or preparing for assignments and exams. The digital platform is embedded in the learning management system and can be used and accessed by students and instructors in all the courses taught each term. In addition, the IT department fully supports the digital platform, and several lecture rooms in the university have the infrastructure needed for optimal lecture recording and streaming.

Despite its several benefits and features for lecture provision, the use of the digital platform in undergraduate courses is not mandatory and its use depends completely on the teacher's decision. During the term autumn 2020, despite the possibility of teaching onsite due to the favourable pandemic situation in Iceland, and the well-managed contagion rate, most of the courses provided were taught online. In response to a sudden increase in COVID-19 restrictions in the middle of September, all the teaching activities were moved fully online. In that term, 390 courses were created in the learning management system. Those courses represented all undergraduate and postgraduate studies across the seven departments in the School of Technology and the School of Social Sciences at Reykjavik University. Among those, only 20% used the digital platform's basic features, such as lecture recordings and slide provision. In fact, only one course included student engagement tools. The potential of the digital platform and its features for improving teaching and learning processes, and supporting the transition to a hybrid or hyflex teaching strategy were also key factors for focusing the programme on Echo360.

7.3.3 The programme

This paper provides an overview of an institutional programme developed in conjunction with multiple factors to act as a link between the social and technical subsystems, namely the instructors' experience, and the digital platform features. The first factor, was the insights obtained from the design phase interviews regarding the teaching practices adopted during the pandemic, their challenges and limitations. The second factor involved the digital platform's capabilities and perceived convenience for addressing the instructors' needs for different teaching modalities. Finally, the third factor was the institutional support, which was provided by the teaching affairs office, as well as the information technology department (IT). The initial intention of the programme was to support instructors in utilising the digital platform, while addressing the high level of inconsistency in remote teaching across undergraduate courses. It was advertised to all teachers in the seven departments at Reykjavik University before the start of the autumn 2021 term. The objective was to recruit at least one participant from each department, to give the programme more visibility, and to include teachers and courses from all departments. The programme was supported by three units at the university: the teaching affairs office, the IT department, and the LA research group based at the Department of Computer Science.

The programme was designed with three main goals: (i) provide the teachers with personalised support and tutorials on the best usage of the digital platform to fit their needs and help them to know and use all the features available, (ii) improve the students learning experience after the pandemic with more consistency among the digital platforms used for teaching and easier access to learning material, and (iii) facilitate data collection, as well as the quantity and quality of data, among years and university departments for future LA research. The programme included the following elements:

(a) **Initial interview:** Before the start of the term, an initial interview with the teachers taking part in the programme was arranged. In the interview, the participants were asked to provide information regarding the courses they would teach in the term autumn 2021, the expected number of students enrolled, and the plan the teacher had for the teaching modality during the term. In addition, we asked about their previous experience using Echo360, the issues experienced, and whether they had any questions regarding the digital platform. Finally, for those indicating they would be using Echo360 for the first time, an initial introduction to the digital platform and its principal features was given. These interviews correspond to the application phase as described in Section 7.3.1. After the interview, the teachers received a set of Echo360 tutorials and recommendations based on the modality they selected for teaching. Neither the tutorials nor recommendations were mandatory to watch or follow, and the participants always had the freedom to decide whether or not to use the features in the digital platform.

(b) **Website:** A programme website was created to store and distribute the Echo360 tutorials for the participants. For the teachers' use, the website includes an (i) introduction to the digital platform, (ii) a set of beginners' tutorials of all the basic features in Echo360, (iii) a set of guidelines and recommendations created to facilitate the students' and teachers' experience using the digital platform, and at the same time to improve the quality of the data gathered, and (iv) a teaching modality subsection. In the teaching modality subsection, the Echo360 features recommended for four teaching modalities were presented: Fully face-to-face, blended, hybrid, and fully online teaching.

(c) **Weekly tips:** Each week from the start of the programme, participants received infographics highlighting one or few features of Echo360 and their benefits. The Echo360 weekly tips were always linked to their tutorial on the website. Figure 7.1 shows two examples of the tips sent to the teachers.

(d) **Feedback:** Following the completion of the programme, the participants would be invited to take part in a final feedback session that would collect their thoughts on the strengths and weaknesses of the programme structure, the tutorials created, and the recommendations received as part of the programme. Feedback would be used to improve the programme, supplement the tutorials, and incorporate the participants' questions into the website's Frequent Asked Questions (FAQ) section.

7.4 Results

In this section, we first present the findings from the interviews in the design phase, followed by a detailed description of the programme's adoption, includ-

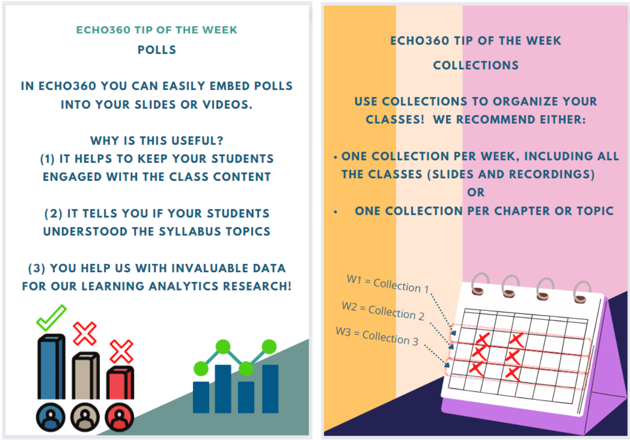


Figure 7.1: Examples of the weekly tips shared with the participants.

ing the participants' courses characteristics, their initial concerns about the digital digital, and the challenges faced during the adoption of the programme. In addition, in regards to the programme results, an overview of the participants' usage of the digital digital is presented, along with the feedback received, and improvements incorporated.

7.4.1 Design phase semi-structured interviews

From the design phase, four main themes were identified: (i) challenges faced, (ii) pedagogical strategies and engagement, (iii) digital technology integration and transition, and (iv) adaptation to remote learning.

Firstly, concerning challenges faced and solutions during the transition period, the professors mentioned technological disruptions, work overload, and technical challenges. In regards to pedagogical strategies and engagement, professors shared the need of real-time digital communication platforms for classes and distance exams. Furthermore, regarding engagement, the professors described the use of quizzes in the assessment structure to motivate the students and keep them engaged with the course content. Regarding digital technology integration and transition, the professors shared their experiences and challenges regarding lecture recording and streaming, and the management of and switching between multiple digital platforms for different purposes. Finally, concerning adaptation to remote teaching, the participants discussed the importance of flexibility in learning environments to adapt to the needs of remote students for both the lectures and practical sessions. Additionally, they shared the strategies followed to adapt their courses to fully online teaching, including both live lectures and pre-recordings. The selection depended on multiple factors, such as the previous experience using the digital platforms, as well as the bandwidth limitations for streaming.

The six professors interviewed in this phase highlighted the use of Echo360 as the digital platform they used for delivering lectures during the pandemic. Among the comments, the technological convenience of the digital platform was also mentioned. As expressed by two of them: *"Previously, I was using Google's live studio, I think it was called. But then I found out that the Echo360 was easier. And they, they could actually set up the schedule for me in advance. So it went from taking a little while to set it up and for it to become basically automatic."* (Participant 1) and *"I can't remember when I switched from studio to Echo360 [...]. At least this switch from studio to Echo, didn't have anything to do with with the pandemic it was more like technological things. There is this that missing back end in studio. It's difficult to search for videos that you've already made and stuff. So the Echo back end, helps you a bit more when you're user."* (Participant 5). Moreover, although most of the professors interviewed used pre-recordings for teaching during the lecture, one of them who had been teaching to remote students for several years and was live-streaming the lectures during the pandemic also mentioned using the digital platform for live-questions in class: *"Well, what changed is that I didn't have students on site for most, most of the semester. So that was a bit different. You could say that I didn't change it so much, but still it meant that instead of getting questions from, from the students in class, I started using basically the Echo360 as a input [...]. Now, I have been using Echo360 in one particular way, which is, besides just recording the lectures, I now use it for the questions in class. So I can embed questions in the slide deck. And then I asked them, the ones that are not there, I asked them to go through the slide deck, and then they get the question coming up, and then they can answer the question [...]. But this is the first time that I actually tried to integrate it into the system."* (Participant 1).

7.4.2 Programme participants

The programme adoption involved seven professors. Table 1 presents the list of participants with information about the department they belong to, the number of courses to teach in autumn 2021, the expected number of students enrolled, and their initial plan for the courses. As shown, the teaching modalities encountered during the term can be summarised in blended, hybrid and fully online teaching; with a mix of synchronous and asynchronous elements. Among the participants, only one of them had previous experience using the digital platform. The professor from the Sport Science department had no courses to teach in autumn 2021, but 4 courses for spring 2022.

Table 7.1: Participants' information, courses, and teaching modalities selected for the term Autumn 2021.

Department	Number of courses	Expected number of students	Teaching modality - settings
Applied Engineering	1	40	Pre-recordings
Computer Science	2	60, and 300	Hybrid
Engineering	2	150, and 200	Streaming and pre-recordings
Business	3	80, 40, and 30	Hybrid/Blended
Psychology	1	30	Fully Online (Streaming)
Law	1	40	Pre-recordings
Sport Science	4	-	Flipped Classroom

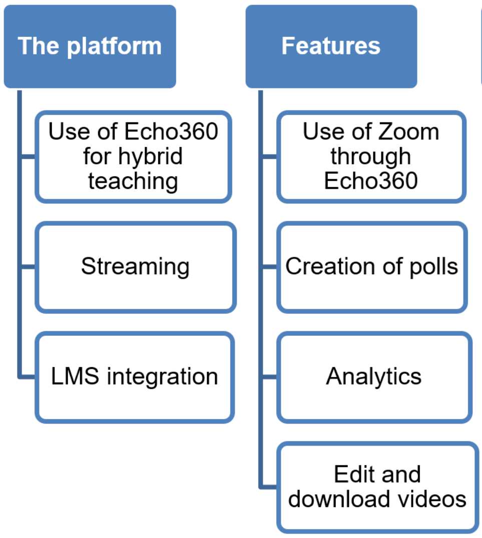


Figure 7.2: Echo360 summary of concerns.

7.4.3 Participants' concerns and adoption challenges

In the application phase interviews, the programme participants brought up a set of questions and concerns regarding the use of the digital platform. Most of the questions were solved during the introduction to the digital platform presented to the teachers after the interview, or through the tutorials provided afterwards. Three main themes were identified among the participants' contributions: The digital platform, its features, and the external resources related to its use. Figure 7.2 summarises the concerns organised by the theme they refer to.

The programme faced several challenges during its adoption. Firstly, the lack of participants from some departments. In order to handle this issue, the Teaching Affairs Office reached out directly to some of the key instructors in those departments to ask them if they would be interested in participating in the programme. This first challenge, was partially a consequence of the summer holidays (which are different for some departments), the pandemic meeting restrictions, and the limited visibility of the programme during the summer. The second challenge faced was the increased workload experienced by the teachers since the beginning of the pandemic. Some authors have investigated the impact of the pandemic on the teachers' experience, highlighting the work overload as one of the main effects on the teachers' quality of life perception [200], [201]. In this programme, the work overload impacted the participation in the programme in several ways. For example, after a couple of weeks one professor decided to stop their participation due to the high workload that importing videos from a different digital platform might represent. The original intention was to hold regular meetings with the participants throughout the term; however, their busy schedules limited the number of activities and meetings that could be arranged. To solve the meetings' limitation, we decided to remove such meetings and implemented the weekly tips described in element c) in the programme.

7.4.4 Participants' usage of the digital platform

Participants in the programme implemented several features in the digital platform throughout the course, depending on the teaching modality and the requirements of the particular course during the term. An overview of the courses' Echo360 sections at the end of the term revealed most of the participants used the basic features in the digital platform, for instance, pre-recordings and slides provision. Moreover, these resources were useful in varied teaching modalities.

Figures 7.3, 7.4, and 7.5 display three examples of the features that were adopted in online and hybrid settings. Figure 7.3 corresponds to an online setting where the professor used pre-recordings to teach the course asynchronously. Two video sources were uploaded, one with the recording of the professor talking while explaining and the second one showing the written explanation of the class topic. Figure 7.4 corresponds to an online synchronous setting, where the professor held the class online via Zoom and recorded the session. The recording was then uploaded to the digital platform along with the slides that were annotated during the class streaming. Finally, Figure 7.5 displays a hybrid setting, where students were allowed to attend in person or join the livestream. The professor included engagement tools (polls) in the lecture slide deck, which was uploaded in advance to Echo360, to gather information about the students' understanding of the lecture topics and to keep the students engaged. Through this process, remote students were also able to become a part of the class dy-

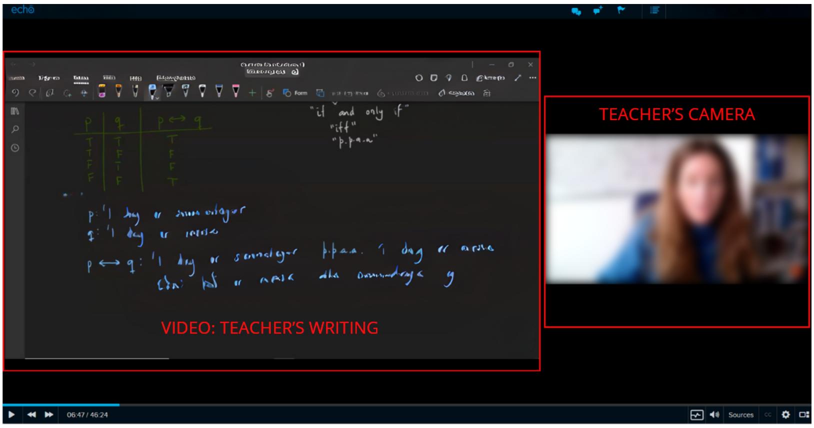


Figure 7.3: Participant adoption example: Pre-recording, including two video sources.

namics. In addition, the class was recorded and uploaded to the digital platform afterwards, since attendance was not mandatory.

In addition, the guidelines, tutorials, and tips shared during the programme, were also beneficial to organise the resources within the digital platform and give them consistent names, allowing students to interact with the digital platform more easily, find specific resources more quickly, etc. There was no formal request for feedback from the students in the groups that the participants taught about the programme or the digital platform, but a few of them provided some positive comments: *"The pre-recordings were nice to have because I could use the spare time I had in between classes to squeeze it in and watch them at a more convenient time"*, *"The polls helped me to at least try and focus on what she was saying. Because I wanted to take part in the polls and show I was actually there"*, and *"I really appreciate that the lectures are available immediately after the class - please show this feature to other teachers :')"*. The comments suggest that the digital platform and the features used supported flexibility and engagement.

7.4.5 Feedback and improvements

There was only one professor from among the seven who took part in the programme who actually offered feedback at the end. In general, both the digital platform and the structure of the programme received positive feedback, *"Overall my experience was very positive, I have some minor niggles which are very small things that I would like, but the ease of use and setting it up inside*

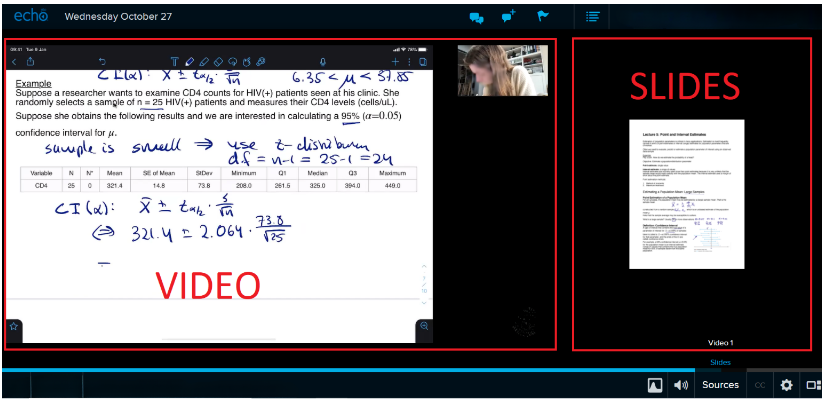


Figure 7.4: Participant adoption example: Online setting and slides.

Figure 7.5: Participant adoption example: Hybrid setting and embedded polls.

the actual labs, like inside the actual lectures going and getting started with the 360 was trivial and really easy and straightforward". In addition, when questioned about the programme and the element that was considered more useful, the professor shared that the initial meeting was for them the most valuable, allowing for a quick snapshot of the digital platform features. The level of engagement after the first meeting, using the weekly tips was also indicated as adequate, as multiple meetings throughout the course would have demanded too much time.

As a first-time user, the participant had some difficulty implementing the digital platform's features into the lectures due to the necessary adaptations and the workload. As the professor expressed, *"I'm teaching all my courses for the first time. So my big focus is not necessarily on using engagement tools or different modalities, but rather just on getting good quality content out there. And I'm going to be hopefully more engaged with the tool you know towards the second-half of next year when I'll be teaching my course for the second time [...], and perhaps it's the wrong approach, but my idea was I need to record these lectures and I want to learn the least amount I need to learn to make this happen".*, pointing out professors teaching a course or in the university for the first time, might face additional difficulties to quickly get used to new digital platforms.

Recommendations for improvement were also provided. Firstly, in regards to the initial meeting, it was recommended to include a demonstration of the engagement tools usage, rather than only describe what engagement tools could be included. The second recommendation, was to include short tutorials, of two minutes maximum, on features that were not included in the initial meeting, for example, how to edit and cut videos in the digital platform. Finally, the professor also shared some difficulties experienced while using the digital platform, such as an automatic device lock after a period of 'inactivity' while answering questions from students in the room. The recording stopped automatically when the computer locked and was automatically uploaded after a few hours, causing confusion among students relying on the recordings uploaded. Both recommendations were incorporated into the website tutorials. The concern raised in regards to the device locking was outside of our control of being resolved, but it was raised as a request to be considered by the digital platform development team to take into consideration.

After the end of the term and the conclusion of the programme, a set of tutorials on the tools available for the students' use was included as a subsection in the website. This subsection included an introduction to Echo360 from the students' view and information about how to interact with the classes and educational material. There were also tutorials for a variety of topics such as joining the classroom live streams, using the question and answer tool, confusion flags, and notes, which could be distributed to the students as well.

Additionally, jointly with the Teaching Affairs Department, an Echo360 workshop was organised at the university. It was during this workshop that the three units supporting the programme presented, explained, and clarified the benefits of using Echo360 to support teaching, as well as how the teachers would benefit by participating in the programme in future terms. To enforce the teachers' willingness to join the programme, a promotional video about the programme was recorded and distributed through several channels, and the Teaching Affairs Office issued a Certificate of Participation to the participants, to recognise their commitment to developing and enhancing their teaching practices, professional knowledge and skills.

7.5 Discussion

This paper describes the development and initial adoption of an institutional programme created to support teachers by providing university-wide instructional material for courses during and after the pandemic. The programme development started in summer 2021, to be implemented during autumn 2021. Seven professors took part in the programme in its first adoption. Tutorials and recommendations were provided based on the teaching modality selected by each participant.

As part of the programme, three objectives were addressed: to assist instructors in using the digital platform to the fullest in accordance with their preferences and needs, to ensure that students' experiences are improved during and after the pandemic by increasing consistency among digital platforms, and facilitate data collection in order to conduct LA research. In this work, we envision the adoption and usage of the digital learning platform as a socio-technical system, where the instructors' needs, preferences, and course requirements constitute the social subsystem, whereas the digital platform features, and the extent to which they can fulfil the instructors' needs correspond to the technical subsystem. In consequence, in relation to the first objective, teacher support material for using the digital platform was created motivated and guided by the professors' challenges faced in remote teaching during the pandemic, the strategies implemented, their experience with digital technology integration and adaptation to remote teaching. In line with research focused on the instructors' experiences during the pandemic, professors at Reykjavik University experienced increased workload [153] and difficulties upholding students motivation and engagement [153], [157]. Moreover, the programme aligned with insights on the pandemic implications for education delivery, specifically the need for faculty training and support for online teaching, and flexibility enhancement [153].

Furthermore, although in this paper we mainly focus on the first objective, some feedback received from students indicates the engagement tools (e.g. polls), as well as the on-demand access to lecture recordings improved the students' experience, by enhancing flexibility in attendance giving them the possibility of re-watching the classes at more convenient times, and favouring their engagement with the class and content. Moreover, since its adoption in 2021, the quality and consistency of data generated within the digital platform have been improved. LA research on students' watching patterns of lecture recordings and access to slides in relation to academic performance [2], and changes in watching patterns under different teaching modalities [3] has been carried out, demonstrating the potential of the programme to support LA research.

The programme presented here not only provides direct benefits for faculty support, but it also contributes to filling a gap in educational research by addressing the lack of emphasis on teachers, compared to the widely studied topics of learners and administrators [202]. Furthermore, as stated above, the set of guidelines and recommendations created to keep consistency in the recordings and material provided through the digital platform not only supported students' learning experience, but also educational data collection. It has been highlighted the need for school support for the improvement of data quality [181] along with thoughtful data creation and storage planning [203]. Our programme contributes to that call from a teachers' perspective, enhancing data quality and quantity, complementing the recommendations for institutions, vendors, and LA researchers' community [203].

Lastly, the university's learning and teaching strategy emphasises the importance of innovation and improvement of teaching methods to effectively support teaching and learning. To that end, this programme is considered as a key element, as it not only focuses on improving the instructors' competences and skills in knowledge communication, but also on improving the students' undergraduate experience by providing them with educational resources that allow them to work independently. This programme sets the basis for transitioning from traditional teaching to hybrid and hyflex spaces where on-site and distance learning students at Reykjavik University will interact within a single programme that adequately addresses their personal needs and preferences.

7.5.1 Limitations

Our work has several limitations, offering multiple venues for further research. First, the programme's development was limited by the educational context in which it was designed. Multiple resources were developed to support education during the pandemic, each of them seeking to address different needs, limiting the direct benefits of the programme to the institution it was tailored to. This is a well known limitation as no 'one size fits all' in educational research [42]. A second limitation relates to the interviews that served as a guide for the initial tutorials that were presented to the professors taking part. As detailed in Section 7.3.1, the six professors interviewed belonged to the Computer Science department. Thus, despite the fact that their courses were among the largest at the university, their experience during the pandemic, the teaching resources used, challenges, and needs might not be as similar as those of professors from other departments. In addition, since its adoption, there have been additional limitations. For instance, the recommendations for keeping consistency in the name given to the recordings and their organisation in the digital platform are not followed if the lecture recordings are automated with the assistance of the IT department, as the names are automatically assigned based on the courses' code in the system. In addition, changes in the digital platform or university policies require regular updates to tutorials and recommendations. Future research will focus on addressing the shortcomings encountered during the adoption, identifying complementary material needed, and assessing the effectiveness of the resources created. In addition, the long-term effects of the programme adoption should be investigated.

7.6 Conclusion

In this paper, we have presented the design and adoption of a university-wide programme created to provide instructors with guidance, recommendations, and support to create, use and share resources according to their specific needs. The programme included four main elements, and was created with three main goals: to support instructors in the creation and provision of educational resources, to improve the students' experience by with more consistency among the digital platforms, and to collect more and better data to support LA research. The findings suggest that the program was adopted successfully and effectively supported instructors' teaching practices. The main contributions of our research include i) an instructor perspective on the digital technology requirements and challenges related to online and distance teaching, and ii) the programme conceptualisation from a socio-technical perspective, where the teachers' experiences and needs during the pandemic are taken into account for the resources included in the programme. Furthermore, researchers and practitioners can use these elements as a guide when developing similar programmes to support instructors in integrating digital educational platforms into their teaching practices.

Chapter 8

Socio-temporal insights on online discussion forum interactions

In this chapter we present a summary of two studies undertaken on interactions occurring through online discussion forums. Three years of data are gathered and analysed from a temporal-network perspective. The chapter is presented in two parts, each featuring the analyses undertaken in each study.

The first is presented as a descriptive analysis of temporal networks' features, published in:

N. López Flores, M. Óskarsdóttir, and A. S. Islind, "Analysis of discussion forum interactions for different teaching modalities based on temporal social networks," in *Proceedings of the NetSciLA22 workshop, March 22, 2022*, 2022, pp. 23–32. [Online]. Available: https://ceur-ws.org/Vol-3258/article_3.pdf
The second one focused on the identification of students at risk of failing through temporal network centrality measures. Currently under review:

N. G. López Flores, V. Uc Cetina, A. S. Islind, *et al.*, "Threads of complexity: Lessons learnt from predicting student failure through discussion forums' social-temporal dynamics," in *Frontiers in Education FIE 2024*, under review, 2024

8.1 Introduction

Learning is not entirely an isolated practice or individual achievement [81]. Instead, it is a socially regulated process [79], where social interactions are essential for the development of skills and knowledge, as the students interact, communicate, and receive feedback from other students and instructors [81]. Furthermore, learning is a dynamic process where the effect of time should be taken into account, as it is not static or instantaneous, but occurs over time [122]. Thus, although learning should be addressed on both a social and temporal level, approaches combining both aspects have been rarely used by educational researchers [204].

Two studies from a socio-temporal perspective are included in this chapter. The first one focuses on exploring and describing the differences in the usage, content, and interaction dynamics in a discussion forum platform used in undergraduate courses under different teaching modalities. It aimed to answer the research question (RQ) *To what extent does the change in teaching modality impact the usage and interaction patterns in discussion forum platforms?*. The second study focused on the identification of students at risk (SaR) of failing. It aimed to assess the predictive power of temporal network centrality measures, and address the imbalanced problem of the SaR early identification. Two RQs guided the second study; (1) *To what extent is it possible to inform the early identification of SaR of failing based on interaction data from online discussion forums?*, and (2) *How does the classification performance compare between traditional oversampling methods and oversampling methods that take the structure of the interactions into account?*

For these studies, three years of forum data were gathered and analysed to outline the changes in interaction dynamics when the modality of teaching shifted from on-site in 2019, transitioning to emergency remote teaching [50] in the middle of the term in 2020, to online teaching in 2021. The data were analysed using a social network approach, by creating three temporal networks, one per year. The temporal networks consisted of twelve snapshots, each of them representing the weekly interactions among the students taking part in the forum threads. In the first study, the temporal networks were used to compare the changes in the dynamics of the group interactions and the posts' features as the term progressed. The second study based on the temporal network under online teaching in 2021 to explore the relationship between activity in the discussion forum and academic performance. In this study, two oversampling methods were employed to address grade distribution imbalance, and the prediction performance of time series classification models were compared.

8.2 Related work

8.2.1 Social and temporal elements of learning

Social Network Analysis (SNA) has been used to investigate several aspects of education; in most cases the students are represented as nodes in the network, and the edges connecting them represent different kinds of relationships or communication events, either online or face-to-face [205]. Among the educational aspects investigated using SNA, the most common are academic success and dropout [83], [87], the influence of homophily on performance [88], [89], Massive Open Online Courses (MOOCs) [86], study patterns [92], course selection [137], [206], collaborative learning [207], and community detection [1], [137], [138]. Data sources commonly used to construct the networks include self-reports and surveys in face-to-face settings, as well as discussion logs and threads in online events and forums for online networks. In asynchronous online discussion forums, students interact with other participants and engage in class-related discussions regardless of time and location [118]. In this way, discussion forums data can be analysed from a network perspective [94], with participants as nodes and messages as links [208], to investigate multiple variables, including post activity [119], interactions [86], topic relevance [119], and student dropout [83].

Learning, like many other real phenomena, is a dynamic practice, as the learning process is not only affected by what happens in the moment. Due to the fact that most educational research has not adequately considered the effect of time on learning activity, the temporal dimension has been underexplored [94]. Such effects relate not only to the moment when the students' activity takes place, but also to the way it happens. Temporal analysis can be used to identify and describe learning events, their variations, metrics, relationships, and transitions [125]. Moreover, undergraduates' self-regulated behaviour and academic performance [123], educational material usage [2], and social connections [86], [208] have been reported to be influenced by time. The study of the temporal element of learning processes and strategies is challenging because it requires measurements over multiple time periods to capture the evolution of its components [209]. A student's approach to learning is also influenced by various factors, including personal characteristics and experience [210]. As affordances between teaching modalities affect students' and teachers' behaviours, it is also essential to consider pedagogical conditions, e.g. course design, digital technology, and delivery method [42].

In addition to the challenges in collecting and analysing temporal and social data, identifying SaR of failing is usually an imbalanced problem. The distribution of grades is affected by several elements, including teaching methods and modalities, grading policies, course design, digital ecosystems, and the students' personal characteristics and backgrounds [5], [45], [98]. Consequently, SaR are not always fairly represented, causing severe biases when implementing predictive algorithms to identify SaR of failing and their learning strategies [45].

8.2.2 Temporal networks and centrality measures

Temporal networks, (i.e., networks where the nodes' connections change over time) are useful for modelling the dynamic behaviour of many complex real-world systems because their interactions are rarely constant over time [211],

[212]. These networks are a particular case of multilayer networks, where each layer represents the connections (edges) between the same group of entities (nodes) at different time points [136]. Temporal networks extend the concepts of static network analysis to include information on when the interactions between the nodes happen [213], which has an impact on several properties and measures, such as connectedness, shortest paths, and centrality measures [214]. Centrality measures are understood as numerical indices that characterise multiple features of the relationships between the participants in a network, their position, importance, and influence [215]. In student networks, centrality measures have been useful to investigate the relationship between a student's position in the network and educational outcomes [94]. However, the effect of the centrality measures on academic performance varies depending on several elements, including course setting, participants background, or the nature of the relationships represented within the networks [120], [216].

Evolution over time is an important dimension in learning processes [123], [124]. Consequently, in the latest years, the attention paid to the temporality and its effects on learning has increased; focusing on varied elements of educational settings [82], [217]. Saqr, Nouri, and Fors [124] studied the role of temporal measures for predicting academic performance; their findings underline that the temporal dimension provides essential information on learning patterns and can potentially support instructors in addressing students' performance. Xu, Lynch, and Barnes [86] implemented SNA and community detection algorithms over data from an 8-week MOOCs course to study the moment when most connections among the students enrolled happen. In their study, most of the connections and communities were created during the first two weeks of the course and evidence of performance homophily was found between the students and their closest friends at the end of the course.

Vörös, Boda, Elmer, *et al.* [218] reported on the collection methodology of a longitudinal data set of undergraduate students, collected from 2016 to 2019. In their study, the undergraduate students answered a set of short and long surveys related to social connections, individual background and study behaviour during the three years of their undergraduate studies. Data from social media platforms and two field experiments were also gathered to complement the surveys' answers. Shirvani Boroujeni and Dillenbourg [143] based their research on online discussion forums in two MOOCs offered by Coursera to analyse the content and social structure dynamics and temporal patterns. Their research shows that activity levels can be predicted one week in advance using the information in the temporal networks.

8.3 Methods

8.3.1 Data and network construction

The studies encompass the discussion forum interaction data of one undergraduate course from 2019 to 2021. The course is a first-year course for the computer science programme at Reykjavik University and a second year course for the engineering programme. The course is always taught in the spring term, with more than 200 students enrolled each year. The main characteristic of this data set is that during the three years included, most of the course's features remained unchanged. The course had the same teacher, syllabus, book, assessment structure, and an active online discussion forum available for the students' use. The only component with significant changes was the teaching modality. The data were accessed and downloaded by the teacher and provided to us with previous permission from the Teaching Affairs Department. When students enrol in Reykjavik University's academic programmes, they are informed that their data can be used for research and informed consent is required. After matching the users with their grades, all identifiable information was removed.

All students enrolled in the course had access to the discussion forum, which was adopted to: (1) encourage the students to collaborate with their classmates, and (2) provide the students with a direct communication channel with the instructors (teacher and teaching assistants). Active participation was highly encouraged, but not required throughout the course. Therefore, students only posted on the board when they needed or desired, resulting in activity on the forum varying significantly from week to week. Students were placed into grade categories based on their final numerical grades; A, B, and C corresponded to grades higher than 87.5, 67.5, and 47.5, respectively. Grades under 47.5 were considered failing and were assigned to grade category D. Due to dropping out from the course or using a non-institutional email address to register for the discussion forum platform, some students were assigned to the 'No grade' category.

The networks were built based on the edge list created using the forum threads archive, as described in Figure 8.1. Each node in the network represents a forum participant (teacher, teaching assistant, or student). The categorical grade placements were included in the network as an attribute of each student node. The interactions in the discussion forum are dynamic, since not all participants registered are present since the beginning, and more edges are added as the course progresses. There are several methods to construct networks based on time-dependent communication events. These methods include binary static networks, in which all communications events in a given timeframe are collapsed into one network, and multilayer networks, in which

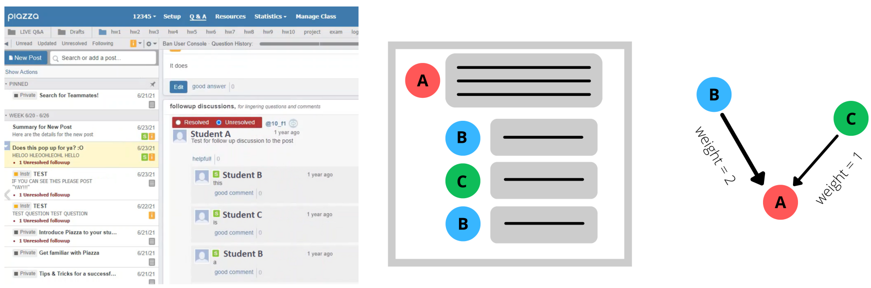


Figure 8.1: Left: Discussion forum snapshot example. Right: Network construction example, nodes represent participants in the forum threads, weights are calculated based on the number of interactions between each pair of nodes.

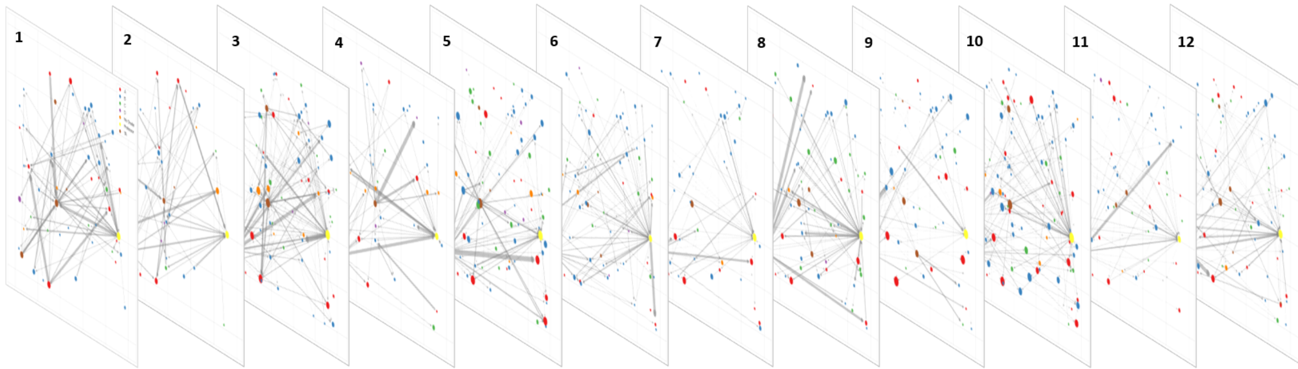


Figure 8.2: Example. Temporal network built based on the 12 weeks of interaction events in 2021. Nodes are coloured based on grade categories, A (red), B (blue), C (green), D (purple), No grade (orange). Instructors, are represented by yellow and brown nodes.

communication events are aggregated based on a specified time window [213]. Following the syllabus structure and the asynchronous dynamic on the online discussion forum; a multilayer temporal network for each year was constructed using a time window of one week. Each layer in the temporal networks represents communication events between forum participants in each of the twelve weeks (Figure 8.2).

8.3.2 Study 1: Descriptive analysis

The first study consisted of a descriptive analysis of discussion forum elements, over three years of data, allowing for comparison of changes between years as well as between teaching methods. It included two components. In the first component, the social network analysis is included with the objective of studying the evolution of communication events throughout the term and comparing it across years and teaching modalities. Table 8.1 displays the network features that were calculated and analysed for all years and networks created. The second component, related to posts' content features, complemented the social network analysis and was useful to get a deeper understanding of the differences between teaching modalities. Table 8.2 displays the features included in the posts' content analysis.

8.3.3 Study 2: Identification of students-at-risk

The second study only included data from 2021 (fully online teaching). The predictive value of temporal network measures was explored through the implementation of time series classification methods. For the classification task, centrality measures were computed for each layer in the temporal network (Figure 8.1). In this study, the content of the posts in the discussion forum is not displayed nor analysed. Sequences of centrality measures for the student nodes were used as input for the time series classification algorithms. The centralities' selection was based on previous educational research. For instance, Saqr and López-Pernas [120] explored the role of centrality measures as indicators of academic success based on data from the online collaboration tasks, showing degree centralities and eigenvector centrality were consistent indicators of academic performance. Furthermore, Saqr, Poquet, and López-Pernas [94] reported that although the study of network centralities in education is extensive, most research is limited to traditional connectivity measures, e.g. betweenness, closeness and degree; highlighting that the inclusion of novel centralities, e.g. Katz centrality, would inform underexplored elements of learning processes. Table 8.3 lists the centrality measures selected along with their descriptions.

There are many factors that influence the distribution of numerical grades in a course. As with other machine learning tasks, unbalanced targets may

Table 8.1: List of network measures computed and analysed in the first component and their meaning in the context of the discussion forum network.

Network Feature	Meaning in the discussion forum's network context
No. of nodes	Number of students taking part in the forum threads by posting or answering threads.
No. of edges	Number of unique edges as an indicator of how active the participants are by contacting different participants each week.
Size	Weight assigned to the edges as an indicator of how strong the connections are. The more communication events occur between each pair of participants, the higher the size will be.
In-degree	Number of peers answering a student's post as an indicator of the nodes' posts popularity.
Out-degree	Number of peers the student answered to by posting an answer or follow-up question.
Density	Number of posts relative to the number of possible students' connections as an indicator of the network's completeness.
Clustering coefficient	Proportion of a nodes' friends answering to each other, as an indicator of how tightly connected the students are.
Teacher's betweenness	Teacher's influence on the information spreading among the course participants.

Table 8.2: Set of features analysed in the posts' content component.

Posts' Feature
Length of the first post in each thread
Number of unique words within the post
Whether the post was published anonymously or not
Time in weeks until a student's first post or contribution
Time in hours until the first answer received to each post
Follow-up questions in each thread
Number of answers provided by the teacher, teaching assistants, and students

Table 8.3: Centrality measures used as input for time series classification models. Selection based on [94], [120].

Centrality	Description
Degree	For a node v, is the fraction of nodes it is connected to.
In-degree	For a node v, is the fraction of nodes its incoming edges are connected to.
Out-degree	For a node v, is the fraction of nodes its outgoing edges are connected to.
Betweenness	For node v, is the sum of the fraction of all-pairs shortest paths that pass through v.
Closeness	For a node v, is the reciprocal of the average shortest path distance to all other reachable nodes in the network. Higher values indicate better connectedness.
Eigenvector	For a node v, it measures its centrality based on the centrality of its neighbours.
Katz	Computes the relative influence of a node v by measuring the number of immediate neighbours and all other nodes that connect to v through them.
Page rank	Computes a ranking of the nodes in the graph based on the structure of the incoming links.

affect the quality of predictions in detecting SaR of failure. A common method to address class imbalance is to randomly oversample minority classes to prevent biases [219]. Although univariate time series oversampling techniques have been extensively addressed to preserve time dependence, multivariate time series data exhibit additional complexity due to the covariance between time series [220]. Moreover, oversampling time series based on centrality measures should take into account both the links between real and oversampled nodes, since centrality measures depend not only on node attributes, but also on the node's neighbours. To overcome the class imbalance problem, we include two sampling methods, random minority class oversampling and synthetic minority oversampling (GraphSMOTE) [221]. The former involves creating multivariate time series of centrality measures from the original temporal network, followed by random oversampling with replacement of minority classes is used to balance the training data and train the time series classifier (see below). In contrast, the latter generates synthetic nodes for minority classes over an embedding space (an encoder) and models their connections using an edge generator. Afterwards, this information is used to train a graph neural network classifier (decoder). We used Deepwalk [222] and Node2Vec [223] to generate feature representations for the networks (Table 8.4), and implemented synthetic node generation and link prediction separately for each layer. After parameters optimisation (Table 8.5), the centrality measures were computed using the augmented adjacency matrix created in the latent space. Thus, we compare two sampling strategies, a naive one (random minority oversampling) to a complex-sophisticated one (GraphSMOTE). The multivariate time series classification models were implemented and evaluated by concatenating the centralities across the 12 layers. Both oversampling techniques were evaluated by randomly selecting 20% of each class in the original data set and setting it aside to ensure that synthetic nodes were not included in the test set. Rocket [224] and K-neighbours [225] time series classifiers were pre-trained and 10-fold

Table 8.4: Parameters list for network representation.

Network feature representation	Parameters
Deep walk	walk_number=10, walk_length=80, dimensions=356, workers=4, window_size=10
Node2Vec Explore	walk_number=10, walk_length=80, p=2, q=0.5, dimensions=356, window_size=10
Node2Vec Stay Locally	walk_number=10, walk_length=80, p=0.5, q=2, dimensions=356, window_size=10

Table 8.5: Parameter grid search for the node oversampling with GraphSMOTE.

Parameter	Grid Search Space
model	{‘sage’, ‘GAT’}
nhid (hidden layers)	{64,128,256}
lr	{0.001, 0.01}
dropout	{0.2, 0.5, 0.8}

Table 8.6: Parameter grid search for the multivariate time series classification.

Model	Grid Search Space
Rocket	num_kernels: {1000, 2000, 3000}
K-neighbours TS	distance: {‘dtw’, ‘euclidean’, ‘squared’}

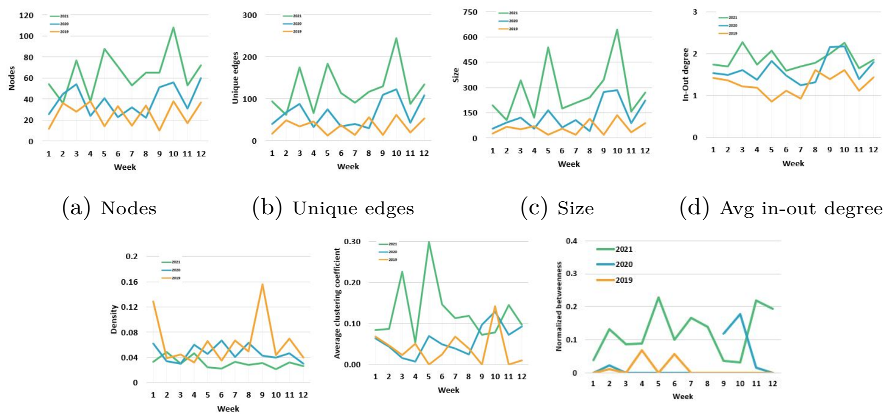
cross validation was used to find the optimal parameters (Table 8.6). By using the Area Under Receiver Operator Curve (AUC) score, we evaluated how well the model could differentiate between classes [226]. The weighted average AUC score for multiclass classification was computed for each class against the rest [227].

8.4 Results

8.4.1 Study 1: Descriptive analysis

The weekly evolution of the network measures in Table 8.1 is displayed in Figure 8.3. Analysing of the evolution of these measures among teaching modalities, along with the analysis of the posts’ features and the forum platform usage among years, lead to the first insights about the effect of the change in the mode of teaching between years. Insights on students activity indicate a higher proportion of students registered into the course’s discussion forum and were active in 2021 under fully online teaching. Moreover, students that were active in the forum under online teaching had on average grades that were 35% higher than students that were non-registered or observer students.

In contrast, although in 2019 and 2020 active students also got higher grades, the positive difference was 5% and 15%, respectively. In regards to the networks features analysed, Figure 8.3 shows the networks in 2021 with fully online teaching grew up faster than the other modalities. Moreover the higher average in-degree, out-degree, and average clustering coefficient in 2021 indicate that students got in contact with more people, and were more connected with their close peers. Finally, the posts features showed the students were more involved in the discussion threads in online teaching, as the number of follow-ups in each thread increased, and the posts were longer and more complex than in previous years. Such changes also provide insights into the instructors activity, showing their workload increased significantly with online teaching.



(a) Nodes (b) Unique edges (c) Size (d) Avg in-out degree

(e) Density (f) Avg clustering coeff. (g) Teacher's betweenness

Figure 8.3: Weekly evolution of the temporal network' measures displayed in Table 8.1 from 2019 to 2021.

8.4.2 Study 2: Identification of students-at-risk

This study focused on the identification of categories A to D. However, 'No grade' students and instructors are considered for the networks' nodes oversampling and centralities computation as they are essential for the information dynamics, as demonstrated in the descriptive analysis. Results of the classification are presented for five incremental time horizons; four, six, eight, ten, and twelve weeks of information, for each timeframe the three node representations (Table 8.4) were considered. Classes A, C, and D were oversampled in both methods, however the number of synthetic nodes created with GraphSMOTE was fixed to be less than the number of nodes of each category in the training

Table 8.7: Performance metrics, network representation, and models selected for the time series classification task for each timeframe. Evaluation metrics AUC (training), AUC (test), and AUC_D (test) for the failed students class are shown.

Weeks	Net. Representation	Model	AUC (training)	AUC (test)	AUC_D (test)
1 to 4	Node2Vec Explore	Rocket	0.5695	0.5360	0.4906
1 to 6	Node2Vec Explore	K-neighbours	0.5716	0.4739	0.4203
1 to 8	Node2Vec Explore	K-neighbours	0.5873	0.5012	0.5042
1 to 10	Deep Walk	K-neighbours	0.5873	0.4194	0.3658
1 to 12	Deep Walk	K-neighbours	0.6100	0.4106	0.3753

set (80%). This was decided to prevent the creation of nodes with redundant information [221].

Temporal sequences were then created by concatenating the centrality measures of all the nodes in each week, and models on Table (8.6) were evaluated. Model implementations based on centrality sequences corresponding to GraphSMOTE for the five timeframes considered showed higher AUCs than those obtained randomly oversampling minority classes. Table 8.7 shows the classification models with the highest training AUC scores along with their performance results on the training and test sets. It is important to highlight that, even though the highest scores were obtained with GraphSMOTE for the five timeframes, the scores obtained and the differences between the training and test scores indicate that although the models performed better when the oversampling was done via GraphSMOTE with Node2Vec (Explore) and Deep walk node representations, the models' performances are still far from optimal and their performance would be affected by unknown biases on the test set. The results suggest that the oversampling method, in conjunction with the classification models implemented, could be used to identify SaR and shed light on the centrality measures that are useful for identifying SaR. However, the data complexity, sparsity and biases could also limit their implementation in practice.

8.5 Discussion

Both the social learning [52] and self-regulation theories [228] attest to the importance of social and temporal aspects; however research that integrates both elements is scarce [204]. In this chapter, we adopt an approach that recognises the jointly influence of social and temporal elements on learning processes. Moreover, the analyses are based on interaction data from an online discussion forum where the students' activity only includes organic contributions. Thus, the weekly activity was truly sparse since participation in discussion threads was neither mandatory nor part of the assessment process.

In the first study, the descriptive analysis of the networks' and posts' features, we compared the impact of the teaching modality on the usage of the forum, and over the participants' interactions. In regards to the RQ stated, it allowed us to notice that the change on the teaching modality impacted not only the activity levels, but also the way the students' and instructors' connected with other participants, as well the comments features.

The second study focused on exploring the extent to which temporal network centrality measures, reflecting the differences in the interaction activity in the discussion forum under online learning, are helpful for the identification of SaR of failing. The approach adopted does not depend on the students' background information, course assessment elements, or the content of the comments posted on the discussion forum. On the contrary, the multivariate time series classification models are implemented using the interaction data and network measures with the objective to identify students in various grade categories. In regards to the RQs guiding this study, the results of the classification models based on random oversampling show that even though prior research in other settings has found this type of data useful to identify SaR [83], [229], [230], this approach does not have the same direct benefit when the data come from courses where the structure is different and the students' participation on the forum is organic. Moreover, the analysis showed that regardless of timeframe, the average AUC was higher when oversampling was performed with GraphSMOTE for training. For four out of five timeframes, the best classification models performed below 0.5 (random baseline) over the test set (AUC_D, Table 8.7). Consequently, activity data are therefore not only imbalanced, but also limited in terms of identifying activity patterns, in line with research on minorities' visibility on social networks, showing that increasing their visibility is not only influenced by group size, but also by group behaviour [231]. In practice, encouraging the students to be more active in the forum would benefit both students as well as the models' implementation and performance.

The learning context of the discussion forum is a limitation for both studies, as it prevents these conclusions to be extended to courses with mandatory or graded forum participation. Additionally, other limitations, including the data itself, are related to the second study. The data is truly sparse throughout the course duration, implying that both the class imbalance and low activity levels have an impact on the performance of the classification models. However, we consider this limitation can also be one of the main contributions of this study, as it reflects the data structure of several undergraduate programmes. To support the adoption of data-driven analyses for improving teaching and learning practices in higher education institutions, research on how to make the most of these data is essential. A second limitation for the second study relates to the course selected and its teaching modality. The descriptive analysis showed the teaching modality affects the interaction dynamics in the discussion forum.

Thus, the conclusions may not apply to courses that adopt a different teaching modality, or course settings. Finally, the low classification performance obtained is seen as the final limitation. The performance score indicates that even though the performance was improved by our method, interaction data alone might not provide enough information to fully identify SaR. However, this approach could be used to boost the classification performance of more complex models that rely on data combined from multiple digital platforms. To extend these analyses, future work would focus on addressing the limitations described, by testing our approach in other educational settings (e.g. MOOCs), as well as including additional data from other sources such as learning materials usage and system logs to evaluate extent to which forum interactions enhance classification models.

8.6 Conclusion

More research is needed to properly account for the effect of social and temporal elements on learning processes in different educational environments. The two studies included in this chapter focus on exploring student $\leftrightarrow$ student and student $\leftrightarrow$ instructors interactions occurring through an online discussion forum. Throughout these studies, we first delved into changes in these interactions and posts features between teaching modalities and throughout the course progression. Building upon this foundation, our inquiry then expanded to explore the predictive value of the centrality measures to identify students-at-risk of failing at different time frames; a complementary yet distinct aspect crucial to further our understanding of the dynamics and value of these types of interactions. This shift not only broadens our exploration but also underscores the complexity of the interactions captured in online discussion forums, highlighting both its potential and limitations for LA research.

Chapter 9

Discussion

This chapter aims to discuss the research findings presented in this dissertation, shedding light on their significance both within the field of research and their value for practical applications. In addition, a conceptual framework and recommendations for the development and adoption of LA research on interactions are also presented, as well as research limitations.

9.1 Overcoming challenges and limitations in LA research

Aside from the implications discussed in Chapters 4 to 8, the overall relevance of the research findings presented in this dissertation can be primarily discussed in terms of how they contribute to addressing specific research challenges and limitations in LA presented in Chapter 1.

Firstly, Chapters 4, 6, and 8 findings shed light on the impact of the pandemic over teaching and learning practices from different perspectives. In Chapter 4 [1], the community detection method applied, along with the communities characterised based on the students' perspectives and preferences about their learning practices, allowed us to provide insights into the extent to which each students' community could have been affected by the pandemic and the sudden shift to ERT [50]. Expanding on the subject, Chapter 6 [3] delves into interaction patterns with the digital ecosystem across the pandemic period, unravelling changes in the interactions observed which were related to the teaching modality, assessment structure, and resources provided. Finally, Chapter 8 [5], [6] investigated the extent to which interactions occurring within an online discussion forum changed throughout the pandemic, in particular, the changes in students' participation and instructors' workload. Integrating these perspectives, the studies provide a comprehensive overview of the significant role of digital platforms and resources in upholding social and material interactions in higher education throughout the pandemic period. Specifically, these results comply with the need to examine learning from different perspectives, namely agency, spatial, temporal, and instrumental [157].

Furthermore, Chapters 4, 5, 6, and 8 provide insights into several aspects of learning temporal dynamics. Social network communities identified and characterised in Chapter 4 [1], shed light on how the dynamics related to students' learning profiles, defined through attributes related to educational values, goals, and teaching methods preferences, evolve as they progress in their undergraduate studies. Chapters 5 [2] , 6 [3] , and 8 [5], [6], focus on the use of educational resources, exploring how and when they are used, and how their usage changes throughout the course progression. In Chapter 5 [2], interactions with lecture recordings and slides are analysed with respect to their use for assignments submission. Likewise, Chapter 6 [3] also explores interaction dynamics with the digital ecosystem, and educational resources. Furthermore, Chapter 8 [5], [6] explores the dynamics of discussion forum interactions under different teaching modalities also evaluating the extent to which such interactions inform the identification of SaR. These findings, taken together, support the expanding field of research on the temporal dynamics of learning [125], [126].

Various shortcomings are addressed in relation to data. For instance, whereas Chapters 5 [2] and 8 [5], [6] explore the value of small and limited data sets and their potential for identifying interaction patterns in relation to academic performance, Chapters 5 [2] and 6 [3] demonstrate the potential for combining data sources from different digital platforms, as well as quantitative and qualitative data, addressing the shortcomings of the number of data sources used for LA research [38], [202].

In addition to the contributions and implications highlighted above in regards to Chapter 6 [3], the chapter presents the design of a data-driven intervention implemented based on the changes observed in interaction patterns throughout the pandemic. A schedule modification was implemented, and the effects on the students' usage of educational resources, academic performance, and experience were evaluated. In this way, the chapter contributes to narrowing the research gap on evidence of LA research implementations in higher education [41], [44].

Moreover, Chapter 7 [4] contributions are valuable to the limited research considering and focusing on the challenges faced by instructors in regards to (1) technology integration into the classroom, (2) teaching practices, and (3) the use of digital technology for learning activities design and orchestration [232]. Furthermore, this chapter contributes to the call for professional development programmes [156], which at the same time served the purpose of facilitating the collection of better data from educational contexts [37].

Finally, in regards to the generalisation challenges discussed in Chapter 1, these studies provide two contrasting viewpoints. On the one hand, they emphasise the need to extend current research to specific learning contexts that have not been explored in detail. For instance, Chapters 6 [3] and 8 [5], [6] demonstrate how changes in the learning context such as teaching modality reflect on the usage of the digital ecosystem elements and educational resources. On the other hand, one of the main conclusions of Chapter 6 [3], relates to the limited effect of changes in the teaching modality over the grade distribution in undergraduate courses. Hence, in alignment with Garrison's view that "distance education is dependent upon communications technology, but effective communication and instruction are considered independent of these devices" [76, p.17], this finding would indicate that the teaching modality selected does not have a direct effect on the students' academic achievement. But equally, insights on the usage of educational resources under different teaching modalitites suggest that an adequate provision of resources is necessary to further our understanding of the extent to which these changes would have an effect.

9.2 Towards a comprehensive framework for LA research on interactions

Drawing connections between all elements and contributions presented above, allows us to critically analyse the significance of such findings and their implications for the investigation of interactions in educational contexts. It is essential to investigate interactions with elements in the learning environment to better understand learning practices and how they change, to facilitate teaching and learning practices that are inclusive, flexible and better tailored to students' needs [97]. To that end, throughout this dissertation, several approaches were adopted to investigate specific types of interactions occurring in higher education, including social network interactions, self-regulation, and socio-technical approaches. Agents, digital platforms, and resources do not exist isolated from each other. On the contrary, they mutually influence each other in multiple ways, as Chapters 4 to 8 exemplify [1]–[6]. From the instructors' perspective, both course requirements and personal preferences shape and influence elements such as the selection of teaching modality, digital platforms used, resources provided, and the assessment structure. From the students' perspective, their background, previous experience with the digital platforms used, time availability, and personality traits influence their interactions with other students and instructors, how they communicate, the digital platforms they use, and the study habits they follow. Furthermore, there are external elements that also influence interactions in educational settings. For instance, system limitations (e.g. limited internet connection), classroom equipment (e.g. projector, cameras, or microphones), and access to other digital resources (e.g.

educational websites, simulators, collaborative platforms, or e-books) could influence the possibilities for teaching modalities, classroom dynamics, and educational resources provided by the instructors. Consequently, it is essential to account for the context in which these interactions occur [233], [234]. Relevant dynamics between social and technical system elements are captured by these contextual relationships, further emphasising the significance of socio-technical perspectives for the investigation of interactions [57].

Several approaches have been proposed to investigate interactions involving different elements. For example, Abreu Saurin and Patriarca [71] proposed a taxonomy of interactions occurring in complex socio-technical systems. The proposed taxonomy comprises nine criteria to classify functional interactions, including the nature of agents and output, levelling, waiting time, distance, degree of coupling, visibility, safety/security hazards, and parallel replications. The taxonomy puts a special emphasis on the system interactions and their variability, allowing for the analysis and classification of functional interactions. Related to interaction in educational contexts, Szeto and Cheng [73] proposed a framework of interactions between in-person and online participants in blended synchronous learning environment. The framework focuses on interactions that emerge in the social presence experience, including verbal and non-verbal interactions between students, instructors, and their interactions with the learning content in blended settings. Nonetheless, although this framework aimed to be used to design synchronous blended learning courses, and accounted for instructor-content interactions in addition to the three types of interactions defined by Moore [74], its focus is mostly in social interactions in synchronous learning environments, with less emphasis on how these interactions shape the students' learning strategies. Chapters 4 to 8 approach these shortcomings, including several teaching modalities comprising synchronous and asynchronous elements, both human-human and human-system interactions, and how they relate to patterns and changes in students' learning strategies and behaviours.

Wang, Chen, and Anderson [72], proposed a conceptual framework for interactions in connectivist learning contexts inspired by Chen's hierarchical model of instructional interactions in distance learning [235]. Chen's model accounts for three levels of interactions each increasing complexity and abstraction, from (i) operation interactions at the foundation level, to (ii) information interactions, and to (iii) concept interactions at the highest level. Under this framework, the interactions addressed in this dissertation can be classified as both (i) operation and (ii) information interactions, which are perceived as complex in connectivist learning contexts [72]. Among these, (i) operation interactions are the foundation and condition for online learning to happen, which can also be extended to hybrid learning environments where most of the information sharing is supported by digital means. Nonetheless, although operation interactions encompass human-machine interactions, these frameworks limit such interactions to learner-media interface interactions without acknowledging the relevance of instructor-media interface interactions. These interactions are essential, as instructors play a significant role in supporting students in developing their learning skills and facilitating the adoption of personalised learning practices, influencing in that way higher interaction-levels [76], [232]. Chapter 7 [4] in this dissertation takes a step further exploring instructor interactions with the system and content from a socio-technical perspective, shedding light on how investigating and optimising these interactions benefit students' access to educational resources. On the other hand, in Chen's framework [235](ii) information interactions include interactions with information and people, namely learner-teacher, learner-learner, and learner-content interactions and are associated with higher levels of engagement and knowledge acquisition [2], [235]. Wang, Chen, and Anderson [72] extended Chen's model to four levels of interactions, including operation, wayfinding, sensemaking, and innovation interactions. In Wang, Chen, and Anderson [72] framework, the interdependence between interaction types is emphasised, recognising that changes to certain interactions have an effect on other interactions despite being at different levels. Although valuable, these frameworks might be limited due to their central scope in online and distance learning, and would need to be extended to account for the current landscape of education after the pandemic. This landscape is to some extent shaped by the positive and negative experiences encountered during the pandemic [153], [156], [157]. Furthermore, in regard to learning strategies, Chapters 4 [1] and 6 [3] provide insights into how students from different profiles might have experienced the pandemic, how the usage of resources differ between teaching modalities, and how the flexibility brought by the hybrid modality and its elements benefited students.

Throughout the chapters included in this dissertation, various types of interactions occurring in educational settings are explored, aiming to provide a comprehensive understanding of their dynamics. These interactions were analysed to explore the extent to which they inform features and changes in undergraduates' learning strategies and behaviours. In addition to interactions with the learning content, it includes interactions that are mediated through the digital ecosystem, where changes in teaching modalities, assessment structure, or resources provided are reflected. From the students perspective, it is how and when they interact with the digital ecosystem. From the teachers perspective these interactions reflect how the system resources support their teaching practices. The exploration of interactions student-student and student-instructor interactions showed how these interactions influence how the resources are used, and how significant they are to support the students. These chapters provide a broader perspective on how the analysed interactions influence each other, as previously discussed.

Overall, the research in these chapters underscores the need for a comprehensive framework that captures the diverse interactions occurring in educational contexts. Nonetheless, there is still a lack of a unified framework or taxonomy aiming to describe all of these interactions, despite their identified dynamic nature in different environments [71]. The development of models and frameworks that capture the complexity of interactions in educational contexts is essential, as it would provide a solid foundation for designing effective instructional strategies and improving learning outcomes. However, these models should be adapted to specific educational contexts and learning objectives in order to ensure their relevance and effectiveness.

In the light of these limitations, one of the main contributions of this dissertation is a conceptual framework that takes the point of departure in the limitations, and in the four years of empirical work alongside the papers on which this dissertation rests [1]–[6]. The resulting conceptual framework for LA research on learning strategies and behaviours from an interactions perspective can be visualised in Figure 9.1. The framework acknowledges the dynamic nature of digital and non-digital interactions as they evolve and influence each other [232].

As digital technology-enhanced resources become more readily available in educational settings, it becomes more important to develop and adopt holistic perspectives on interactions. The framework considers the dynamic nature of interactions and the role they play in studying varied modalities, providing a foundation for both LA research on learning strategies and behaviours and the design of effective instructional practices and interventions. It comprises two levels, interaction level and institutional level. Interaction level is primarily inspired by Chen [235] and Wang, Chen, and Anderson [72], considering operation interactions as the basis for information and concept interactions [235], and the interdependence between these interaction types [72]. Nonetheless, it also underlines the influence of instructor-digital ecosystem/content interactions over learning strategies and behaviours [76]. Six additional elements are included in the framework, divided between interaction (human perspective, dynamics of learning, and value of data) and institutional level (technological infrastructure, institutional support, and data governance). These elements are included due to their role for supporting LA research from an interaction perspective. Whereas elements at interaction level are essential for the development of LA research on interactions, elements at institutional level contribute to both purposes, the development and adoption of LA research on interactions. These elements underscore both implications for research and practice discussed throughout this chapter, and are further described in Section 9.4.

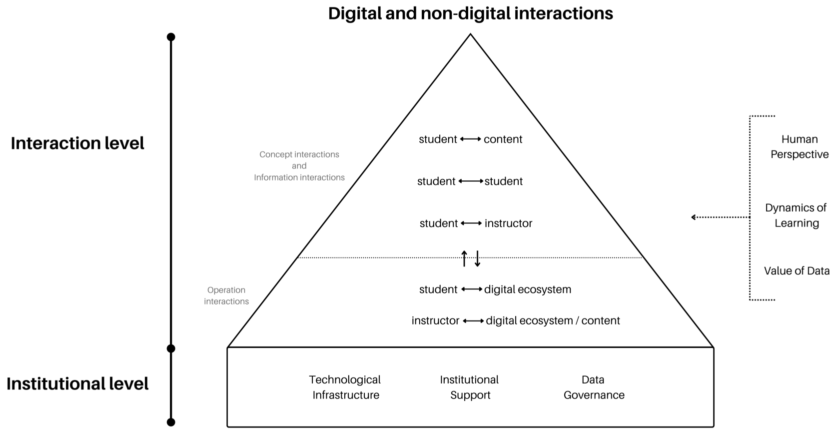


Figure 9.1: Conceptual framework for LA research on learning strategies and behaviours from an interactions perspective.

9.3 Implications for a more cohesive practice

This subsection delves into the practical implications of the research findings presented, with the aim of highlighting the potential for actionable recommendations in real-world settings. Consequently, the research chapters included throughout this dissertation demonstrate their value for improving teaching and learning practices as well as LA adoption in the specific context in which they have been developed. The particular challenges faced also provide valuable insights for the improvement of the conditions that would support the development and adoption of LA research.

Practical implications in regard to data

Firstly, from Chapters 7 [4] and 8 [5], [6] recommendations can be drawn in regards to data collection, data quality, and quantity. In particular, reviewing the way the users interact with the digital platforms, their needs, and the benefits they get from the digital platforms sheds light on potential ways to collect more and better data. For instance, in these chapters, gaining a better understanding of the instructors' needs and limitations for streaming and recording lectures allowed us to provide resources to address such needs, thus making it easier for them to use the digital platform (more data). Understanding the limitations of the data for the LA research could also shed light on alternative ways to collect better data and benefit students at the same time. For instance, in Chapter 7 [4], initial reviews of the data coming from the platform Echo360 not only showed instructors' usage of the digital platform was limited in the sense of the available tools, it was also revealed that the way in which the instructors were using the digital platform was not consistent. This lack of consistency affected both using the data from the digital platform in combination with other platforms, as well as the students' experience with the digital platform, where the current settings made it difficult for them to sort, and find information about specific topics or teaching weeks. Consequently, the creation of guidelines and recommendations for instructors to use the digital platform in a more consistent way favoured both the development of LA research and the improvement of the students' experience. Moreover, these reviews should also include a full mapping of how their interactions can be better linked across platforms. The second example belongs to Chapter 8 [5], [6]; the analyses of the discussion forum showed that not only the low level of interaction with the forum threads, and potentially low levels of students' engagement (especially failed students) limited the extent to which these data can inform the identification of SaR, but also shed light on to the benefits of being active in the forum threads. Consequently, encouraging students to be more active in the forum could on the one hand support the students to access valuable information about the course through the discussion forum, and at the same time increase data quality and quantity for LA research.

Practical implications in regard to resources

Implications for practice also extend to the provision of support resources. In the first place, recommendations on the provision of resources for instructors can be drawn from Chapters 7 [4] and 8 [5], [6]. As in Chapter 7 [4], by understanding the way in which teachers use digital platforms, resources and recommendations can be created, allowing them to use digital platforms more efficiently, quickly, and appropriately. Alternatively, descriptive analyses in Chapter 8 [5], [6] showed variations in the workload experienced by instructors under different teaching modalities brought by the increase of both the students active in the course, and the number of posts and follow ups created in the forum. As shown in these studies, considering the teaching modality helps to dimension the extent of resources needed by instructors, not just in terms of technical or physical resources, such as the adequate technology for lecture streaming or recording; but also human resources, such as hiring enough teaching assistants to support teaching activities and students' support in external digital platforms.

Furthermore, recommendations about the provision of resources to support students' learning strategies and behaviours can be derived from studies presented in Chapters 4 [1] , 5 [2], and 6. Whereas in Chapter 4 [1] the study profiles outlined highlight differences in the students' preferences regarding learning resources to use, such as preferring to attend the lectures at the university premises instead of watching lecture recordings or vice versa, Chapters 5 [2] and 6 [3] shed light into differences on how and when the students use such resources. Consequently, the provision of resources to enhance flexibility both in attendance and learning activity is considered essential. The need for such resources to support students and enhance flexibility has been demonstrated, but further exploration of the underlying factors influencing non-high achievers' use of these resources is needed to identify potential resources that can be used to support them. Examples of such resources include supporting the students in becoming familiar with the digital platforms available to them in each course, ensuring they know which platforms are being used by the instructors, how to access and use them and how to access the learning resources in those digital platforms if needed.

Practical implications in regard to support

Another set of implications for practice relates to the institutional support needed. Participation of different stakeholders, including not only academic, but also educational development, information technology, and administrative stakeholders is needed to ensure the successful development, adoption, implementation, and evaluation of LA research and findings. For instance, for development, support for accessing, collecting, and safely storing data from institutional systems and digital platforms is needed. Consequently, administrative and information technology stakeholders should be involved to provide the adequate infrastructure, to grant access to relevant data and platforms, and ensure the data collected is used responsibly and in compliance with relevant privacy and ethical guidelines.

The involvement of educational development stakeholders is essential throughout the LA life cycle. Their insights on the teaching and learning environment, institutional values, and resources available can contribute to the design and implementation of effective LA interventions. Furthermore, both administrative and educational development active involvement in the implementation and adoption process is crucial for growing faculty and student participation. Examples of how their active participation would benefit LA research can be found in Chapters 4 [1], and 7 [4]. In Chapter 4 [1], data from an online survey distributed to the students in 2019 was used to build a student social network and characterise study profiles through the community detection methods. From 2021, and throughout the course of this doctoral research, efforts have been made to collect data from a similar survey. Students were invited to take part in the survey at the beginning of each term. To increase their participation levels, some professors agreed to advertise the survey and granted some lecture time for the students to answer the survey. Efforts to achieve this objective were supplemented by distributing gift cards through raffles for participants, as well as promoting the survey through multiple communication channels such as emails and announcements in university corridors. In Chapter 7 [4] on the other hand, the programme created to support instructors in creating and providing educational resources was created with support of the educational development office to promote the programme among the university departments.

Overall, the implications discussed in this section can guide instructors towards more cohesive teaching practices. For instance, teaching practices can be enhanced through the use of digital technology for providing resources, while also taking into consideration different student profiles and how their profiles can be supported through digital platforms. For example, providing lecture recordings can benefit students who prefer to watch lectures on their own, cannot attend in person, or need to revisit the material at a different time. Similarly, the provision of resources such as quizzes and polls can be beneficial in maintaining students' motivation and engagement, while also allowing them to become familiar with the learning content. Furthermore, discussion forums offer additional communication channels between students and instructors. Additionally, participation in institutional programmes that support instructors and their teaching practices can be beneficial for course management and improvement.

Finally, it is important to emphasise that from the standpoint of adoption and implementation, LA will not be successfully embraced merely by the efforts of a single individual or department. On the contrary, systemic and institutional support is essential for such implementations. For example, the schedule modification implemented in Chapter 6 [3], thanks to the support from professors and university administrators.

9.4 Recommendations for development and adoption of LA research from an interaction perspective

The implications for research and practice discussed above provide the basis for proposing a set of recommendations for supporting the further development and adoption of LA research.

Recommendations for adoption

In regards to adoption, three key recommendations are drawn. These recommendations are included in the framework at institutional level (Figure 9.1).

- Technological infrastructure: The provision of adequate technical resources to support current teaching practices and facilitate alternative teaching methods when necessary. Special emphasis should be placed on technological resources that enhance flexibility and selection of educational resources and learning strategies.

- Institutional support: LA adoption would benefit from the active participation and engagement of institutional departments involved in learning and teaching practices, including academic, educational development, and information technology departments.

- Data governance: The creation of a well-outlined data governance programme is essential for the adoption of LA research. It should consist of policies and procedures aimed at ensuring data quality, management, privacy, security, and accessibility. Regulatory compliance should also be taken into account to protect sensitive information and personal data.

Recommendations for development

The recommendations presented above, which are also essential for LA development, are complemented by the following recommendations aimed at facilitating the investigation of interactions in higher education. Accordingly, these recommendations are included in the framework at interaction level (Figure 9.1).

- Dynamics of learning: A comprehensive investigation of interactions in educational contexts should account for the influence of temporal and social temporal elements. Such effects and influence should be investigated both individually and combined to better understand how they shape learning strategies and behaviours.

- Value of data: Data comes from a wide range of sources and it is recommended that various sources of data be considered in the learning environment. Exploring the value of data (not just big data), recognising the value of small data sets from digital educational platforms would benefit the development of LA research. Furthermore, the study of interactions can be enhanced by exploring ways to combine multiple quantitative and qualitative data sources.

- Human perspective: The development of LA benefits from acknowledging the human perspective involved in several interactions, including human-human, and human-system/content. This perspective can provide insights into elements that may be overlooked or undervalued in other approaches, identify areas of improvement and user needs.

9.5 Research limitations

It is important to acknowledge the inherent limitations of this research. Firstly, in regards to the type of interactions addressed, throughout the chapters included in this dissertation, elements of machine-machine [236] or content-content [75], [76] interactions, such as their limitations and influence on learning strategies and behaviours are not explored. Additionally, no investigation has been conducted regarding instructor-instructor [75], [76] interactions. The inclusion of these types of interactions should be considered for further research.

As a second concern, the use of self-reported measures and information, such as declared social ties, perspectives, and personal experience with digital platforms and resources expressed in semi-structured interviews, may lead to biases in the analyses, affecting their validity or reliability. For example, self-reporting social ties could be biased by students stating more social ties that are actually less meaningful to them than they claim. Furthermore, information gathered through semi-structured interviews may be biased towards positive (or negative) outcomes, resulting in a misrepresentation of certain outcomes.

In the third place, in this dissertation the term “lecture recordings” is used without distinguishing between pre-recordings, lecture recordings in hybrid settings (recording of the streaming), or lecture recordings in on-site settings (recording of the lecture). Although the type of recording provided is related to the teaching modality as Chapters 5 and 6 explore, investigating the differences among these types of recordings, their influence on learning strategies, or pedagogical implications were out of the scope of this dissertation.

Finally, the timeline in which this research took place is another noteworthy limitation. While providing valuable insights into the effects of the pandemic on teaching and learning practices, it also implies limitations for generalising to other contexts. The educational environment in Iceland during the pandemic differed from those in other locations due to the restrictions, availability of resources, and size of the student population.

Chapter 10

Conclusion

"A través de la educación, encontré la palabra libertad."

— Eufrosina Cruz Mendoza

"Through education, I found freedom."

— Eufrosina Cruz Mendoza

10.1 Main contributions

This dissertation presented five chapters focused on exploring different types of interactions in higher education to investigate learning-related strategies and behaviours. In their own way, each of the studies contributes to answering the research question that runs throughout this dissertation: *How and to what extent can the analysis of interactions be used to inform features and changes in undergraduates' learning strategies and behaviours?*

In Chapter 4, we explored the extent to which community detection methods applied to social networks built based on declared students' social interactions inform the characterisation of undergraduates' study profiles. We identify and characterise five study profiles, providing insights into how these profiles might evolve as the students progress in their studies and acquire more experience and connections. We also provide insights into how and to what extent different study profiles might been impacted by the pandemic outbreak.

In Chapter 5, we explored what differences were present between high and low achievers in terms of the use of educational resources in relation to assignment submission. By combining data sources we shed light on the relationship between usage of resources, assignments submission, and academic performance.

In Chapter 6, we explored changes in the students' usage of the digital ecosystem when the pandemic hit as well as the extent to which a data-driven schedule intervention was helpful to support the students' learning activity. We found changes in the way the students organised their time and activity during the pandemic. The evaluation of the intervention implemented showed the intervention did not impact the grade distribution and how the new schedule and the resources provided impacted the students' learning experience.

In Chapter 7, we presented the design and initial adoption of an institutional programme to support teachers in creating and providing educational materials. Furthermore, the programme aimed to support students' learning experience by increasing consistency among courses and material provided, facilitating data collection, and improving the quality and quantity of data.

Finally, in Chapter 8, we explored interactions that occurred through online discussion forums under different teaching modalities. We showed how temporal network measures reflect changes on the teaching modality, providing insights into the instructors role in communication. Moreover, based on the interactions occurring under fully online teaching modality, we explored the extent to which network measures are helpful to inform the identification of SaR of failing. We found that, despite their potential, such implementation is highly limited by the data sparsity and complexity brought by the nature of the interactions happening in the discussion forum.

Three key contributions can be summed up in this dissertation. Firstly, in relation to the research question and the study of interactions in educational contexts, each of these chapters as summarised above sheds light on the way these interactions relate to the learning strategies and activity. From one perspective, interactions can shape or influence the students' learning activity; for example, students' social connections and the resources provided by instructors through the digital ecosystem or content. From another standpoint, students' interactions with and through the digital ecosystem and its elements reflect students' learning strategies and changes in their behaviour, providing valuable insights to support them. Overall, along with a set of practical implications, this dissertation outlines an overview of these interactions and their relationship with learning strategies. Based on the dissertation findings and implications, the research question finds its answer in the conceptual framework for LA research on learning strategies from an interactions perspective presented (Figure 9.1).

The second key contribution relates to LA research. The overall perspective provided by the studies in this dissertation as a whole, contributes to the LA broader objective by providing insights into (i) students behaviours, interactions, and the usage of course material, (ii) personalised and effective learning experiences, (iii) the identification of inefficient behaviours and potential improvements of course design, as well as (iv) interventions in educational settings [60].

Lastly, the third key contribution is associated with the effect of the COVID-19 pandemic on teaching and learning practices in higher education. In this dissertation, insights on this element and its impact are explored from three viewpoints, including the students, instructors, and digital ecosystem usage throughout the pandemic.

Ultimately, the studies included in this dissertation are helpful resources to deepen our understanding of interactions in the context of Icelandic undergraduate programmes. In turn, this has the potential to inform the development of effective pedagogical strategies for this context, by extending our understanding of the way digital technology and resources available in digital ecosystems are inextricably linked to educational practices [232].

10.2 Future work

As Chapters 4 to 8 conclude with a discussion on future research opportunities to the respective project, this section presents additional projects and research directions beyond what has already been discussed.

10.2.1 Longitudinal evolution of study profiles

In the research conducted thus far, interactions pertaining to students' learning strategies and behaviours have been explored, shedding light on their temporal dynamics, as discussed in the previous chapter. Specifically, in four out of the five chapters included, insights related to temporal changes in study profiles and strategies are provided and analysed. Longitudinal data collection of students' social networks is challenging and the availability of longitudinal open data sets of students' social connections is limited.

Throughout the development of this doctoral research, efforts were made to gather data on how students' social networks change as they progress in their undergraduate programmes. From autumn 2021 to spring 2024, six rounds of data collection on students' social ties were conducted. The students were invited to take part in the study, thus their participation was not mandatory although it was encouraged by the professors as well as gift cards giveaways. Nonetheless, the response rates of each students' cohort were not high enough to allow for longitudinal analyses of changes in social ties to be conducted.

Overcoming these data limitations by improving response rates on students' social networks has the potential to make significant contributions to the field as it would offer several opportunities for further research on interactions in higher education. For instance, a first possibility already being explored in collaboration with other universities in Iceland; focuses on investigating social influence effects on study profiles and learning preferences, motivation, engagement, and academic attrition. Furthermore, this study would also provide valuable insights into the relationship between academic performance and social connections over time. Furthermore, it would also be possible to examine whether networks constructed based on interactions with digital ecosystems or educational resources can be utilised to replicate students' social networks.

10.2.2 Socio-temporal data augmentation

Students' social interactions are essential for emotional wellbeing and sense of belonging in higher education [237], [238]. Additionally, as they are related to academic engagement, performance, and attrition [52], [239] their investigation offers many opportunities to inform the identification of SaR. Furthermore, students' social connections are not static; rather, they can change over time for a variety of reasons [123].

Thus, the use of temporal network measures for performance prediction through quantitative analytical methods would potentially inform not only the identification of SaR (as in Chapter 8) but also, depending on the measures included, could be useful to identify patterns and trends in students' engagement over time, as well as to inform the development and implementation of interventions to support students.

In that sense, in contrast to the models implemented in Chapter 8, the development of homophily-based network augmentation strategies specially created taking into consideration the characteristics of social networks in educational contexts has the potential to support the implementation of classification models by addressing the grade distribution imbalance. Consequently, the development of these augmentation strategies would lead to better representations of the original data in the augmented training data set. This would reduce overfitting and improve prediction performance in small data sets.

10.2.3 Interactions with generative AI-based educational resources

In light of the increased proliferation of generative artificial intelligence (AI), the imperative need for a better understanding of the dynamics and patterns in human-machine social systems has been highlighted [236]. In alignment, the increased availability of AI-based tools and their adoption in educational contexts have raised multiple concerns in the academic community since their release. While some concerns relate to implicit biases in the algorithms used for these tools' development, other concerns pertain to their impact on teaching and learning practices, academic integrity, data privacy, and institutional policy [240], [241]. Although these tools, for instance writing assistants, were not specifically developed for their use in education, they have the potential to transform teaching and learning practices [242]. Consequently, it is essential to gain a deeper understanding of how students and instructors interact with these tools. This will enable us to better assess the potential risks and benefits of their adoption in educational contexts, inform the development of revised teaching methodologies, and provide support for institutional policy development.

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Appendix A

Declaration of authorship contribution

The table below is intended to serve as a template for how much effort was involved by the Ph.D. student in the various stages of a publication process of a research article. What is excluded in the table is what role the Ph.D. student had, i.e., whether the Ph.D. student took the lead in the project, coordinated it, acted as the driving force, handled all administration, etc. or not. The idea is therefore that one of the following abbreviations (ME, EE, CE or LE) should be entered in each box. Below the tables, a brief explanation is given for each column in the table. This declaration of authorship contribution is to be submitted to the RGCS in the Computer Science department.

- ME = Main effort, includes the main effort in the indicated column.
- EE = Equal efforts, includes that there was a shared equal effort between with at least one other author of the paper (this can for instance be the case when the work behind the paper was divided or when co-authorship has been equally divided between at least two authors).
- CE = Contributing effort, entails important effort but there is someone else in the author list that delivered the main effort.
- LE = Learning effort, includes an effort of a learning character, for instance by assisting with the data collection or assisting with the analysis. At least a LE is needed in all columns to fulfil the Vancouver rules for authorship.

Paper name	Idea	Related work & literature	Data gathering	Research Design	Artifact Design	Analysis & synthesis	Draft	Administration
Paper 1								
Paper 2								

Idea = Crystallising and formulating a clear and novel research idea alongside research question(s) or hypothesis.

Related work and literature = Reading up on the relevant literature and related work, finding the relevant references as well as putting them together in a coherent manner alongside building up the research gap.

Data gathering = The gathering of data for the paper.

Research design = Decide on how the data gathering should be conducted (randomised clinical trial, qualitative data gathering, mixed methods, devices used for data gathering or quantitative data gathering for instance).

Artefact design = In case there is a theoretical model, a method, a digital artefact of some sort (or any type of software), requirements to be tested or an algorithm (or machine learning model) that was developed then this category would cover it.

Analysis and synthesis = The analysis of the data alongside the discussion and main contributions drawn from the analysis.

Draft = The first finished draft of the paper.

Administration = Includes all work with the administration of the publication, such as the submissions of the multiple revisions alongside communication with editors, major effort in writing the revision comments for journal papers and all communication and inclusion of all authors in the various revision rounds.

Appendix B

Addressing questions and comments posed by thesis committee members

About Chapter 4: Exploring Study Profiles of Computer Science Students with Social Network Analysis

- Why was the Girvan-Newman algorithm selected?

  Throughout the development of this analysis, two community detection algorithms were evaluated initially: label propagation and the Givan-Newman algorithm. The former identifies communities by spreading labels based on the dominant labels in the neighbourhood. To do so, each node adopts the label that most of its neighbours currently have. Although it has the advantage of being fast and scalable in large networks, it is a non-deterministic algorithm that can produce different communities when it is run multiple times over the same network. In contrast, the latter is a deterministic modularity-based algorithm. One of the main limitations of this algorithm relates to its scalability, as the need to recursively recalculate betweenness makes it computationally expensive for large networks. This issue is mitigated by modularity-based methods such as the Louvain algortihm that implements greedy optimisation to make the betweenness recalculation fast and efficient. In the paper, considering the characteristics of the network analysed and communities identified by these algorithms, results from the Girvan-Newman algorithm were presented.

- What are the conditions under which this algorithm can be applied? Such as maximum number of nodes, maximum number of edges, what hyper-parameter can be set by the user, etc.

  The algorithm itself does not involve a lot of hyper-parameters to be tuned compared to other algorithms. Nonetheless, some of the elements involved can be adjusted based on specific requirements in the analysis. These include, (a) the number of communities to be identified, (b) the stopping criterion, which can be the optimised modularity or the number of edges removed, and (c) the recalculation frequency of the edge betweenness, which can be complete or partial once an edge has been removed.

  In regards to the maximum number of nodes and edges, they directly impact the algorithm's computational complexity. Its complexity is $O(m^2n)$ where n is the number of nodes and m is the number of edges. The practical size limit is often determined based on the computational resources available. However, the algorithm is considered generally feasible for networks containing a few thousand nodes and edges.

About Chapter 5: Making the Most of Slides and Lecture Captures for Better Performance: A Learning Analytics Case Study in Higher Education

- In general I think it is possible to train a predictor based on the time the student spent using the educational material. One question would be: how many weeks would we need to observe the students' patterns of accessing the educational material to be confident of our predictor model?

  The duration needed to observe student patterns for a reliable predictor model could vary depending on the context being analysed. In the structure of the course analysed in this chapter, the quizzes were included in the last 6 weeks (out of 12) of the term. I consider that although this fact does not necessarily would limit the predictor performance it could limit the possibility of developing interventions to support the students. Nonetheless, I consider the analysis you suggest really interesting, it would be worthy to evaluate the effect of time on predictors while incorporating data from multiple sources.

- (About discussion on the high achievers activity) In Fig. 5.3 but in (a) the high achievers have lower median ratio than the non high achievers.

Thanks a lot for highlighting this, you are right. Fig. 5.3 includes students with activity in the lecture recording platform, whereas Tables 5.4 and 5.5 describe the activity of all the students in the course. The discussion should have clarified this.

About Chapter 6: A Learning Analytics Driven Intervention to Support Students' Learning Activity and Experiences

- Regarding the adjustments performed in the way the courses were taught, I would ask: should we consider other variables such as whether a student has a job or not? Maybe the student adjusted due to job constraints, family-specific needs, etc.

  This is an interesting observation. Although the provision of lecture recordings enhances flexibility in accessing the learning resources evaluating this element and how these students use the materials is an intriguing research question. The analysis presented was developed throughout the COVID-19 outbreak, which also implied limitations in work attendance as it did for education. However, to the best of my knowledge, the course schedule remains in its modified form. Thus, I consider that subsequent analysis could include the validation of the findings presented in this chapter in the years following the pandemic, while incorporating the variables you suggest.

- One more thing to consider is that many students spend time watching other external educational resources, such as YouTube videos, that they consider better for their learning strategies or as supporting material.

  As you mention, resources that the students can freely access online can boost how well students understand academic topics. However, including data from external sources implies several challenges. For instance, the variability and diversity of the content offered in these platforms make data collection and the analysis of watching activity related to assignment submission challenging. Privacy concerns for data collection should also be considered, as the process of obtaining these data could involve intrusive monitoring.

  I consider that the investigation of these interactions is definitely worth exploring in the future. Upcoming studies could explore effective methodologies for integrating these data, potentially through surveys, self-reports, or collaborations with these platforms to better understand and quantify their impact on learning processes.

About Chapter 8: Socio-temporal insights on online discussion forum interactions

Relevant points to consider in the analysis of results include:

- The sparsity of the interactions is a problem for the algorithms.

  Thanks for highlighting this, it is indeed one of the biggest challenges to be addressed in follow up analyses. As you mention, the natural sparsity in the data represents a problem for the algorithms. Finding a way to address this issue is crucial for improving our models and extracting insights from the data that are valuable for informing the identification of students at risk.

- Some students may prefer to interact less on this type of forums and it does not imply that they are not learning the content or that they will have a low score.

  I totally agree with this comment. Indeed that is something that can be inferred from the context we study in this chapter. Insights from the descriptive analysis in the first study indicate that students who do not post can have good grades. Nonetheless, active students showed average grades 35% higher than non-active students. Furthermore, I consider that additional information, such as reading behaviour could also be incorporated and provide further insights to improve the identification of students at risk. Unfortunately, the discussion forum platform used does not provide data describing this reading behaviour. However, data from the learning management system could be used as an indicator of frequency in accessing the forum and incorporated as an additional variable into the model.

- Adding other features to these networks may increase the performance in the prediction of students at risk of failing, features such as the time the student spends reading the educational material shared by the instructor as shown in Chapter 5.

  This is an excellent recommendation for the following studies. I consider merging data from the three main elements in the digital ecosystem:

Table B.1: Additional performance metrics for models in Table 8.7.

Weeks	AUC	Accuracy	Precision	Recall
1 to 4	0.5360	0.2388	0.3168	0.4355
1 to 6	0.4739	0.1862	0.2736	0.1936
1 to 8	0.5012	0.2347	0.3352	0.2258
1 to 10	0.4194	0.1367	0.2116	0.1613
1 to 12	0.4106	0.1280	0.1948	0.1451

Weeks	AUC_A	AUC_B	AUC_C	AUC_D
1 to 4	0.4273	0.5998	0.4960	0.4906
1 to 6	0.4636	0.4995	0.4628	0.4203
1 to 8	0.4728	0.5277	0.4660	0.5042
1 to 10	0.4545	0.3913	0.4810	0.3658
1 to 12	0.4364	0.3741	0.4810	0.3753

the learning management system, Echo360, and the discussion forum platform would be helpful to improve the classification performance.

- (About Table Table 8.7) Why did you not use the same model for all the weeks? In $AUC(test)$, are you trying to classify A, B, C and D but in $AUC_D(test)$, are you trying to classify D or not D? If so, is it not surprising that AUD_D is lower? It would be good to see a confusion matrix.

For each timeframe, we used the AUC scores in the training test to compare model-network representation pairs. The model-network representation with the higher AUC was selected. For the AUC scores, both correspond to scores over the test set. $AUC(test)$ corresponds to the weighted average of the four individual AUC scores (A to D) computed as 'one vs. the rest'. $AUC_D(test)$ corresponds to the classification of the D category. As you mention, four out of five scores were lower compared to the weighted average, indicating that the models could not identify this category in the same way as the others. Unfortunately, the confusion matrices were not stored for these runs. Table B.1 displays additional performance metrics for the models.

About Chapter 9: Discussion

- (About Chapter 7 findings discussed in section 9.1) At least here, at the University of Iceland, we were more "forgiving" when giving grades in the pandemic. The final grades were pretty much the same between years but the requirements were not.

This is something that we had the chance to discuss with the professors teaching the courses included in Chapter 6. As you mention, these professors indicated that some ways of ‘relaxation’ were adopted during the pandemic. Examples include, less strict deadlines for assignment submissions, simplification of classes and assignments, or additional multiple-choice quizzes and exams to motivate and support students. In the specific course where the change in the class schedule was implemented (1_A), the professor indicated that their way to support students was by being extremely detailed and specific in the explanations and videos to ensure the students could follow the course content, while keeping the assessment structure without changes.