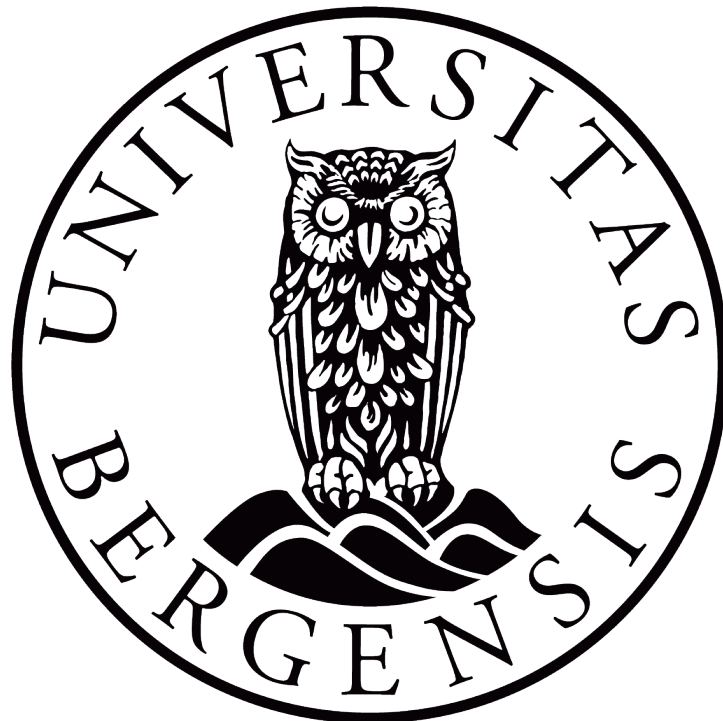


eduGraph: A Dashboard for Personalised Feedback in Massive Open Online Courses

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A master's thesis in Information Science

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27.05.2022

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Abstract

Learning Analytics is concerned with designing and implementing tools and processes for collecting, analysing, and communicating information about teaching and learning. It is enabled by data but not driven by it; instead, it tries to empower human judgements by presenting meaningful facts. This thesis explores the data generated in Open edX courses to understand how it can be analysed and used to impact learners' motivation in online courses. It is carried out using Design Science, a research methodology aiming to produce artefacts that can improve the interaction with problems.

In this thesis, I present the eduGraph dashboard, which uses Learning Analytics to present meaningful insights about learners' learning process in Massive Open Online Courses (MOOCs). Results indicate that learners perceive the dashboard as valuable and effective at motivating them to participate in online courses and that it enables them to keep track of their progress in the courses. I posit that the biggest problem facing Learning Analytics today is the lack of accessible data and that it is possible for researchers to create more accurate learner models by using Learning Analytics theories and methods in combination with the iterative and technical process of Information Systems development.

Keywords: learning analytics, self-regulated learning, online courses, Massive Open Online Courses (MOOCs), dashboard, personalised feedback

I have no special talent. I am only passionately curious.

- Albert Einstein, 1952

Acknowledgements

While writing this thesis for my master's degree, I have had the opportunity to work with and receive support from many people. I want to thank all of you for your support, time, and effort.

I want to thank my main supervisor **Prof. Barbara Wasson** for her support and excellent feedback on the project. Your guidance has been greatly appreciated.

This endeavour would not be possible without the support of my co-supervisor **Dr. Mohammad Khalil**, who has been instrumental in the development of this project. Your guidance and support have been invaluable in helping me understand the problem space and how to solve it. Furthermore, your guidance in tough times has been invaluable in helping me overcome the difficulties that I faced.

A major thanks to **Gleb Belokry**s for all the technical help that he has provided in the development of eduGraph, and for your quick adaptations to the challenges we faced.

Special thanks to **Ann-Karin Valle** at Oslo Metropolitan University for her support and enthusiasm in the development and deployment of eduGraph. I am also grateful to all the students who participated in the evaluation of eduGraph, and their valuable feedback and suggestions.

I'm incredibly grateful to my parents and sister for their unending love and support. Thank you for being by my side, no matter where you are.

Lastly, I could not have undertaken this journey without the support and friendship of my amazing friends, Dennis Fossen and Johann Bugge.

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Acronyms

AA Academic Analytics. 20

AI Artificial Intelligence. 20

API Application Programming Interface. 14, 51, 52, 54, 57

BI Business Intelligence. 20

CLI Common Language Interface. 52

CLR Common Language Runtime. 52

CSS Cascading Style Sheets. 54

DM Data Mining. 21, 22

DS Design Science. 5, 9, 11, 35, 36, 37, 38, 39, 45, 69, 70, 75

EDM Educational Data Mining. 20, 21, 22, 26

HTML HyperText Markup Language. 54

HTTP HyperText Transfer Protocol. 51, 53

HTTPS HyperText Transfer Protocol Secure. 51

IDE Integrated Development Environment. 53

IS Information Systems. 15, 35, 37, 38, 69, 77, 78

ITS Intelligent Tutoring Systems. 19, 20

JSON JavaScript Object Notation. 51, 52, 57

LA Learning Analytics. 5, 16, 17, 18, 19, 20, 21, 22, 25, 26, 27, 32, 33, 39, 48, 73, 74, 77, 78

LAD Learning Analytics Dashboard. 15, 16, 22, 24, 25, 48, 55, 71, 72, 73, 77, 78

- LMS** Learning Management System. 15, 18, 19, 20, 22
- LTI** Learning Tools Interoperability. 58, 60, 74
- ML** Machine Learning. 21, 22
- MOOC** Massive Open Online Course. 5, 6, 15, 16, 17, 18, 25, 26, 72, 73, 74, 77, 78
- MOOCs** Massive Open Online Courses. 15, 73
- MVP** Minimum Viable Product. 42
- OAI** OpenAPI Initiative. 52
- OAS** OpenAPI Specification. 51, 52, 57
- OsloMet** Oslo Metropolitan University. 15, 44, 49, 55, 58, 60, 69, 74
- OXALIC** Open edX Advanced Learning Analytics Tool. 18, 57, 58, 77
- REST** Representational State Transfer. 14, 51, 52
- RESTful** RESTful API. 51, 52
- RPC** Remote Procedure Call. 51
- SAKI** Self-Adaptive Keyboard Instructor. 19
- SLATE** Centre for the Science of Learning and Technology. 15, 18, 55, 57
- SOAP** Simple Object Access Protocol. 51
- SPOC** Small Private Online Course. 18, 26
- SRL** Self-Regulated Learning. 5, 16, 17, 27, 29, 31, 32, 33, 39, 47, 48, 72, 74, 77, 78
- UiB** University of Bergen. 15, 18
- VCS** Version Control System. 49
- XML** Extensible Markup Language. 51

Chapter 1

Introduction

The explosive growth of Massive Open Online Courses (MOOCs) in the last few years, especially the push for increased digitization of learning during the COVID-19 pandemic, has created a greater supply of data about learners, from which we can learn about their behaviour in courses and gain insights into their learning (HolonIQ, 2020, 2021; Impey, 2020). Increased usage of mobile devices to perform learning-related tasks, more Learning Management System (LMS)s, and social media have led to a more significant portion of learning activities generating digital trails (Siemens, 2013). LMSs and MOOC platforms such as Moodle, edX, and Open edX generate millions of data points for learners visiting the course material of the systems. These data points include navigation in the system; play, pause, and seek events when viewing lectures and videos; quiz answers; discussions on forums; and other interactions with the course. These data points may be ambiguous, but for researchers and education stakeholders in general, these data points offer opportunities to explore the learning habits of learners in new and exciting ways.

1.1 Motivation

The research presented in this thesis contributes to the "Better Learning Experience" (BLE) work led by Dr Mohammad Khalil. BLE is a project initiated in collaboration between the Centre for the Science of Learning and Technology (SLATE) from the University of Bergen and Oslo Metropolitan University (OsloMet) to employ Learning Analytics in several courses provided by the Department of Nursing and Health Promotion. OsloMet has internally funded the project to utilise Learning Analytics to understand learners' behaviour in MOOCs. In addition, one of the project's main goals is to support learning and ease teaching feedback to learners. This thesis has contributed to the understanding of learners' behaviour in online courses and provides a Learning Analytics Dashboard (LAD) for learners to receive personalised feedback on their learning. As Information Systems development has always been of interest to me, this thesis is my attempt at providing a solution to an interesting problem and

make learning more engaging and personalised in online courses. I am sure that the continued development of this research will lead to a better understanding of learners' behaviour in online courses and a better learning experience for learners.

1.2 Research Questions

This thesis explores how the data points generated in Open edX courses can be analysed and used to impact learners' motivation and performance and present a dashboard for personalised feedback in MOOCs. The following research questions are addressed:

1. What data can be extracted from an edX platform to support learner motivation through a LAD?
2. How can a dashboard be designed to increase learner motivation and performance in MOOCs?
3. How do learners perceive a LAD designed to track their progress and increase motivation?
4. How can Learning Analytics enable personalised feedback in MOOCs?

1.3 Structure of the Thesis

This thesis is structured as follows: in Chapter 2 the background of the project is presented. Central to this Chapter are research areas of Learning Analytics and Self-Regulated Learning. In addition, the Open edX platform and MOOCs are also presented. Chapter 3 describes the methodologies used to conduct the research and Chapter 4 presents the development process of the eduGraph dashboard. In Chapter 5 the evaluation of the dashboard is presented before discussing the findings of the research and answering the research questions in Chapter 6. Finally, a conclusion is presented in Chapter 7, followed by the future direction of eduGraph.

Chapter 2

Background

This chapter reviews selected literature relevant to the research in this thesis. First, a background on the platforms, tools, and Learning Analytics (LA) is given before turning to research on Self-Regulated Learning (SRL).

2.1 MOOCs, edX & Open edX

2.1.1 Massive Open Online Courses

MOOCs are online learning environments that allow a virtually unlimited number of learners to enrol in free online courses. The term was first used in 2008 by Stephen Downes and George Siemens and has since then seen rapid growth in popularity (Baturay, 2015). As of 2022, there are hundreds of millions of enrolments in MOOCs in tens of thousands of courses ranging from entry-level to university-level courses in many different subjects. One of the fundamental characteristics of MOOCs is that they are free and open to anyone with access to the Internet. The work produced during the course by teachers and learners is shared and made publicly available in forums and discussion boards. There is also transparency regarding the learners' involvement in the course. Cormier and Siemens explain, "When learners step through our open door, they are invited to enter our place of work, to join the research, to join the discussion, and to contribute in the growth of knowledge within a certain field." (Cormier and Siemens, 2010). Participation in MOOCs is not limited to the course itself, but the entire community of learners. Participation enhances the learning process by allowing learners to create and share personal contributions and engage with other learners' efforts. Finally, MOOCs are distributed platforms. As MOOCs are built on a connectivist philosophy, any knowledge generated should be shared throughout the network of participants. The majority of learners' time is spent in social learning environments, where learners interact with the subject and each other's perceptions about it. Therefore, the role of the course material is to serve as a starting point for thoughts and debates.

2.1.2 edX

edX is one of the most popular non-profit providers of MOOCs, created in a collaboration between Harvard University and the Massachusetts Institute of Technology. edX offers university-level courses in various academic fields to learners worldwide and researches learning using big data generated on their platform. edX's mission is to "Increase access to high-quality education for everyone, everywhere," and to enhance and improve teaching and learning in digital arenas through research on their free, open-source Open edX platform (edX, 2021). As a leading provider of online learning, edX has more than 40 million users with a combined 110 million enrolments in more than 3600 courses.

2.1.3 Open edX

Open edX is edX's free, open-source platform for creating massively scalable LMSs. It offers institutions of higher education, government organisations, and individuals the tools and platform needed to create and distribute their own MOOCs and Small Private Online Course (SPOC)s. Unlike the biggest providers of MOOCs today like Coursera, Udacity, and Udemy, which boast many courses and enrolled learners, Open edX has mainly been used to offer smaller classes, modules, and SPOCs. SPOCs are private courses with a smaller number of learners while still maintaining the same philosophy that is used in most MOOCs. SPOCs offer many benefits by incorporating MOOC technology into this environment, allowing learners to engage in more face-to-face (online) sessions and receive personalised feedback from teachers.

2.2 OXALIC

OXALIC is an Open edX Advanced Learning Analytics Tool developed by the Centre for the Science of Learning and Technology (SLATE) at the University of Bergen (UiB), as "a standalone Learning Analytics tool for the Open edX MOOC platform." (Khalil and Belokry, 2020). OXALIC is a web application that provides a platform for several groups of stakeholders to collect data from the Open edX platform and to provide useful representations of the data collected. Due to the nature of the collected data, privacy and consent are a must for the data to be useful; therefore, the main group of the first version of OXALIC is teachers and researchers. Teachers can see learners' interactions with the course and track their progress, allowing teachers to make early interventions to help learners improve their performance based on the information presented in OXALIC. Furthermore, rich visualisations of the data collected are useful for researchers to support teachers in understanding learners' learning habits. In the long run, OXALIC aims to create a robust and useful technical solution for learning analytics in MOOCs, introduce new branches of LA, and provide an easy to use tool for its stakeholders (Khalil and Belokry, 2020).

2.3 Learning Analytics

Learning Analytics (LA) is an emerging field that is concerned with sense-making and action in teaching and learning. As defined in 2011 at the first International Conference on Learning Analytics, LA is a set of techniques and tools for collecting, analysing, and communicating information about learners in a variety of contexts, “for purposes of understanding and optimising learning and the environments in which it occurs.” (SoLAR, 2022). It has the power to transform current methods of teaching and learning through studies on learner behaviour and learning outcomes, allowing more effective pedagogical strategies and supporting learners’ self-efficacy and control over their learning (Slade et al., 2019). While still an emerging field, LA is a promising area of research that is rapidly expanding and moving towards widespread adoption across the entire education sector.

2.3.1 History of LA

LA as a concept can be traced back to the first automated teaching machine, developed by Pressey in the 1920s (Pressey, 1927). His work on Intelligent Tutoring Systems (ITS) laid the foundation for one of the areas of science that LA draws upon. Another influential area has been cognitive science, from which the first adaptive teaching system known as the Self-Adaptive Keyboard Instructor (SAKI) was developed in the 1950s. SAKI was developed to teach keyboard skills by aligning the difficulty with a learner’s performance (Pask et al., 1961). Although this initiative was elementary by today’s standards, it did demonstrate how learners’ learning may be assisted through the use of large-scale technology. The growing realisation of the benefits of personalised instruction has had a significant impact on the development of modern educational technology and, by extension, LA. Bloom’s groundbreaking “two-sigma” study in 1984 found that learners in individualised learning conditions performed one standard deviation better than learners in mastery-teaching conditions (Bloom, 1984). This, combined with incredible technological advancements of the period, resulted in significant success in the fields of ITS and computer-assisted instruction. Although such systems were considered cutting-edge and revolutionary at the time, their specialised nature, and thus expensive development and production costs, were a barrier to their widespread adoption (Joksimovi et al., 2019).

The explosive digitization of learning from the early 2000s led to the development of LMSs, web-based distance learning technologies. They are increasingly being used to complement traditional brick-and-mortar classroom-based learning, allowing new forms of learner engagement. Teachers can incorporate online activities and assessments in their face-to-face teaching with LMSs. LMSs and similar technologies, while similar to ITSs, are more flexible and adaptable to the needs of the learners, allowing for a wider choice of instructional styles, contexts, and disciplines. Furthermore, their much lower development and production costs

and the minimal set of required technical skills to create and distribute them have allowed LMS-based technologies to expand into all aspects of education rapidly.

George Siemens notes that LA is a multidisciplinary field with roots in several disciplines (Siemens, 2013). While the fields of Artificial Intelligence (AI), Educational Data Mining (EDM), Academic Analytics (AA), and Business Intelligence (BI) are vital to the development of LA, several other fields and disciplines within education have contributed to the emergence of LA as a discipline. *Citation analysis* allows us to see how research is disseminated and validated, and in the context of education, it is essential in mapping knowledge domains. Instead of treating all users the same, *user modelling* contributed to a shift in computing where users are more directly associated with their distinct personalities, goals, interests, and so on (Rich, 1979). User modelling has been essential in human-computer interaction research. It allows researchers to understand better how individual differences between users in traits, goals, and motivations affect their interaction with computers (Fischer, 2004). *Education/cognitive modelling* has been applied in LA to trace how learners develop knowledge and have historically aimed at creating systems with a "computational model capable of solving the problems that are given to learners in the ways learners are expected to solve the problems." (Anderson et al., 1995). One key component in supporting learners in the learning process is to model cognitive processes, allowing intelligent tutors to be developed. *Adaptive hypermedia* expands on user modelling by enhancing personalised content and interaction, adapting to the needs of learners based on their goals, preferences and knowledge, and presents an important future direction for LA.

"While intelligent tutors, user modeling, and adaptive hypermedia emphasized research challenges in learning," (Siemens, 2013), BI was applied to the academic sector by AA. While AA is commonly referred to as LA, its BI roots are more concerned with optimising organisational procedures, such as personnel management, resource allocation, and increasing the efficiency of universities.

2.3.2 Learning Analytics Tools & Processes

Since the early days of Pressey's work on ITS (Pressey, 1927), we have come a long way. We have already touched on one of the most widely used platforms for LA tools, the LMSs. These systems are vital to the collection of data for use in LA and are what enable the field of LA to be rapidly expanding. The tools and processes used to collect, analyse, and communicate information in LA are described in the following subsections.

Data collection

LA requires data. Data sources that reflect the complexity of learning processes are required for efficient and effective analytics of learners' behaviour in learning environments. "Simply

put, 'quality' data are required." (Siemens, 2013). "High-quality" data will allow researchers better to understand the social and pedagogical components of learner performance. Unlike contrived learning environments, where learners are forced to complete tasks, learning environments where learners are engaged in authentic learning activities (where data collection is unobtrusive) are more likely to produce high-quality data. LA builds on the foundations of EDM for much of its data collection.

Educational Data Mining

EDM is an established interdisciplinary field of research that applies statistical, Machine Learning (ML), and DM methods to various forms of educational data. Its main goal is to study this type of data to answer problems in educational research problems. EDM is concerned with developing tools for exploring the unique sorts of data found in educational settings and, by doing so, better understanding learners and the environments in which they learn, improving education and facilitating research on education (Romero et al., 2010; Romero and Ventura, 2010). Romero and Ventura state in their review of the state of the art of Educational Data Mining that the EDM process is about converting raw data into useful information that can impact research and practice in education. EDM allows researchers and practitioners to discover knowledge about learners' usage of systems to evaluate the impact on learning outcomes. While EDM has its roots in DM, there has been relatively little research on education in the field of DM. Some key points that differentiate how DM is applied to other domains outside of education from EDM are:

- *Goal:* DM goals heavily depend on which application area it is being used in. In EDM, the goal of each application differs based on the orientation of the system towards different actors. Some applications are oriented towards learners, where the goal is to recommend activities and tasks that improve their learning and engage them in learning experiences. Other applications are oriented toward teachers, where the goal can be to improve the quality of teaching (Romero and Ventura, 2007). Furthermore, DM has been used in LA to develop analytics systems for building learner models and profiles that can be used to forecast success or identify at-risk learners, intervention techniques, and adaptive learning strategies (Siemens, 2013). Different orientations for EDM applications lead to objectives being difficult to quantify and necessitate a unique set of assessment technologies.
- *Data:* Data in traditional DM applications typically includes data such as access logs for servers and web applications, but also more complex data about the habits and interests of clients. On the other hand, data in educational environments are available for mining in many different types. These data are educational-specific; therefore, they have inherent semantic information, connections to other data, and numerous degrees

of meaningful hierarchy. It is also essential to consider the pedagogical aspects of the learning environment, such as the objectives, activities, and the learner itself.

- *Techniques:* Traditional DM has mainly been concerned with the use of statistical methods and ML techniques such as clustering, classification, correlation, and regression to extract information from data. Successful application of these techniques has already been proved in the educational domain. Nevertheless, educational systems and data have unique characteristics that necessitate the subject of EDM to be tackled in a different way than typical DM, which has led to EDM developing more advanced techniques. As a result of the issues with data hierarchy and nonindependence in EDM, psychometric methods designed to address these concerns have been developed. However, seeing as EDM still is an emerging field of research, further development of new - and improvement of existing - techniques are expected to result in a better understanding of the unique challenges faced by researchers in EDM (Romero et al., 2010).

Learning Analytics Dashboards

The increasing use of LMS to complement traditional, brick-and-mortar classroom-based learning has led to many LA applications. Several dashboards have been developed to support both learners and teachers. According to Few, LADs give graphical representations of a learner's current and historical state of learning, allowing for quick and precise decision making (Few, 2006). Initially, a dashboard is a control panel placed within the central console of a vehicle or small aircraft, displaying instrumentation and controls for the vehicle's operation (Wikipedia, 2022). However, due to the influence of information technology, the utilisation of dashboards has expanded, and educational dashboards as a sense-making component of LA systems have received much attention (Verbert et al., 2013). LADs are web-based applications that allow teachers to monitor learners' progress in learning activities and provide feedback on their performance. In 2006, Few introduced several examples of functional versus ineffective dashboard designs based on his practical experiences and theoretical foundations, and defines a dashboard as "... a visual display of the most important information needed to achieve one or more objectives that has been consolidated on a single computer screen so it can be monitor [sic] at a glance" in his book "Information Dashboard Design: The Effective Visual Communication of Data" (Few, 2006).

Dashboard Design

Effective dashboard design is a challenge that requires careful consideration when developing a dashboard. Critical components of an effective dashboard can be found in Few's definitions of a dashboard and are discussed further in Park and Jo's paper on "Factors that affect the success of learning analytics dashboards." (Park and Jo, 2019). Park and Jo found that

dashboards' aesthetic appeal and usability directly and significantly impact the level of understanding and perceived usefulness and, therefore, the dashboard's success. Furthermore, it was found that learners' understanding of the dashboard directly impacted their behaviour changes. Therefore, effective dashboard design should be based on theoretical foundations of human cognition and perception and should be designed to be intuitive and with ease of use in mind. Few notes three special considerations from the literature concerning the visual perception of dashboards (Few, 2013).

To begin with, humans have limited working memory and can at most hold three or four bits of visual information at one time. As a result, well-designed displays, such as graphs, are better for efficient perception and memory retention rather than individual figures when designing a dashboard. Second, form, spatial position, and motion should be appropriately employed for quick perception. According to Gestalt's principles, aspects like proximity, similarity, continuity, and connection should also be considered. Finally, the dashboard's design should be based on the user's needs rather than the needs of the system. The implications for the dashboard design are that the information should be presented logically, with each aspect supporting the learner's immediate and long-term objectives for decision-making. Furthermore, the visual representations must fit on a single screen, and the most critical information should stand out from the rest.

Feedback in Dashboards

The feedback provided by the dashboard is a critical component of the design of a dashboard and should be based on the learner's current state of learning and their long-term goals. Several concepts exist for providing feedback to the learner, as outlined by Sedrakyan et al. in their paper on "Linking Learning behaviour Analytics and Learning Science Concepts" (Sedrakyan et al., 2020). Central to research on feedback is the regulation of learning and performance as a goal-oriented planned and metacognitive activity. Learners take control of their behaviour, thoughts, and motivation to complete a task (Zimmerman and Schunk, 2011). According to Zimmerman and Schunk, successful learners employ a variety of strategies to guide and enhance their learning process to complete academic assignments. Feedback should guide learners in setting goals, organising learning, and providing insight into their progress to allow them to make better decisions for their learning process. Furthermore, it should define and clarify what is considered good performance to make it possible for learners to benefit from it (Sedrakyan et al., 2020). It should also allow learners to reflect on how to act to close the gap between their current and desired performance and provide a framework for learners to assess how their current performance relates to their desired performance.

According to research by Irons and Elkington, the earlier learners receive feedback on their progress, the more helpful it is for their learning (Irons and Elkington, 2021). Therefore, the feedback should inform learners as soon as inefficiency or difficulty in learning occurs,

thus stimulating learning regulation. This can be achieved by, for example, providing learners with relevant resources that might help progress on their learning tasks or engage them in a discussion about the problem that they are experiencing. Furthermore, teachers should also be informed when multiple attempts at regulation do not lead to significant progress, which might point to a lack of understanding of the task, allowing teachers to provide more specific feedback. Most psychologists and educators agree that learning is a combination of two processes, *explanations* aimed at improving understanding (cognitive), and *guidance* to influence behaviour (behavioural). Learning is a multifaceted process; therefore, these are often combined (Sedrakyan et al., 2020). Different kinds of cognitive feedback, such as corrective, epistemic, and suggestive feedback, have been identified in previous studies (Alvarez et al., 2012). *Corrective feedback* informs learners about the quality of their work and usually provides alternative solutions to the problem. Epistemic feedback solicits and inspires critical explanations and clarifications by asking learners to explain their work further. *Suggestive feedback* is a form that is more direct and specific and gives the learner suggestions on how to progress and an invitation to explore further or improve their work. Different types of feedback can also be used together; however, they should be applied in the context of the task at hand. As opposed to cognitive feedback, behavioural feedback aims to change the learners' behaviour, intending to improve their awareness of the learning progress and the ability to regulate their learning process better.

As a result of the theories covered above, feedback in LADs should allow a learner to keep track of their progress and support them in the process of goal selection, monitoring, and "providing increased awareness on overall progress toward goal achievement and possible needs for regulation" (Alvarez et al., 2012). This emphasises the need for measuring learners' goals and plans to inform them about their progress.

Existing LADs

Verbert et al. (2013) present an overview of 15 dashboard applications for learning in their article "Learning Analytics Dashboard Applications". In the presented overview of the dashboard applications, it was concluded that most of the dashboards support either teachers or both teachers and learners. Of the 15 dashboards presented, only four were explicitly designed for learners. The remaining 11 dashboards were designed for teachers or both teachers and learners. Evaluation of the dashboards indicates that retention rates in learners with access to a dashboard are significantly higher than those without access (96.71% vs 83.44%, respectively) (Verbert et al., 2013). Although the results are encouraging, only the evaluation of one dashboard, Course Signals (K. Arnold and Pistilli, 2012), impacted learning. Similar studies with other dashboard applications are necessary to confirm the impact of dashboards on learning. While this is promising, the impact on learning is still hard to demonstrate and evaluate, and more research is highly needed.

LAD Issues

A successful dashboard would impact learners' self-regulation and their learning behaviours and outcomes (Park and Jo, 2019). Research suggests that LADs contribute to self-reflection and strategic action for learners through indication of discrepancies between the goals and the current state of learners' progress (Kim et al., 2016). However, according to Sawyer (Sawyer, 2014), most educational dashboard applications lack theoretical support from learning sciences and an evidence-informed foundation for choosing the best data to identify the needs of learners. As a result, most dashboards today focus on where learners are doing well, how much content they have engaged with, and their progress compared to their peers. This has a low impact on increasing learners' engagement and motivation to complete tasks, and therefore, many of the designs suffer from improving engagement and learning for learners (Blumenfeld, 1992). The scarcity of theoretical grounding found in "the learning sciences and research on feedback and underlying mechanisms of learning processes" (Sedrakyan et al., 2020) is most common to those prioritising feedback for LADs, as reported in the literature on dashboards. Previous studies have typically examined dependent variables such as learning achievement (Chen et al., 2008; Kosba et al., 2005), retention rate (K. E. Arnold and Pistilli, 2012), and perceived usefulness (Dollar and Steif, 2012; Santos et al., 2012) to verify the effects of LADs. However, although there has been a rapid increase in LA research for dashboards, there is little evidence that LADs are designed to support teaching and learning.

2.3.3 LA Challenges

Data interoperability "imposes a challenge to data mining and analytics that rely on diverse and distributed data," (Bienkowski et al., 2014), which is the type of data generated in MOOCs. As Verbert et al. state, "although an enormous amount of data has been captured from learning environments, it is a difficult process to make this data available for research purposes." (Verbert et al., 2012). Furthermore, sharing available data is a challenge because of issues regarding privacy, the variety of data sets and sources, and the absence of standardised data representations. Analytics researchers, therefore, have a substantial obstacle in the form of dispersed and fragmented data because the data trails generated by learners are collected and stored in a variety of different systems, databases, and formats. Furthermore, the interactions that learners have with the content, one another, and software systems cannot be analysed as a unified whole since these learner experiences are not recorded. Suthers and Rosen sum up the difficulty in analysing data from MOOCs. They wrote that "since interaction is distributed across space, time, and media, and the data comes in a variety of formats, there is no single transcript to inspect and share, and the available data representations may not make interaction and its consequences apparent" (Suthers and Rosen, 2011).

Any online or digital interaction generates a data trail, and ownership of that trail has not

been resolved either culturally or legally. However, privacy and data ownership are not exclusive to LA, and as the World Economic Forum notes, access to data "is generating a new wave of opportunity for economic and societal value creation." (Forum, 2011). This economic value can be generated in higher education by improving teaching and learning, reducing learner attrition, and enhancing support services. As the interactions occur in a borderless and global online environment, any strategy for exchanging data and data privacy demands a global view (Forum, 2011). Additional issues surrounding the implementation of analytics in educational settings are mirrored in the broader privacy and ethical concerns that have surfaced due to the rapid advancement of online technologies. The legal system has not entirely addressed new opportunities brought about by technological advancements in many different domains, including copyright and intellectual property law. Privacy regulations vary from country to country, resulting in different problems when, for instance, a learner from Norway enrolls in an online course with a provider located in the US. In the not-too-distant future, rules and laws on privacy may require a harmonisation comparable to the one that has occurred for copyright and intellectual property laws in many industrialised countries over the previous several decades.

Although it is evident that LA can offer teachers and professors insightful and practical information regarding their teaching and the learners' performance, the repercussions of placing significant reliance on analytics are not entirely transparent (Khalil et al., 2018; Prinsloo et al., 2019). The process of learning is fundamentally a social activity and cannot be reduced wholly to algorithmic representations. Education encourages original thought and calls for the formulation of novel strategies, ideas and principles. On the other hand, the focus of analytics is on locating and elucidating what already exists. Even though software systems might be capable of representing the creative potential of learners in the future, even agent-based simulations today are incredibly simplistic. George Siemens sums it up nicely, "the tension between innovation (the generation of something new) and analytics (the evaluation of what already exists in data) is one that will continue to exist in the foreseeable future." (Siemens, 2013).

2.3.4 Conclusion

As a research field, LA can be said to sit at the convergence of learning, analytics, and human-centred design, and is concerned with the design and implementation of tools and processes for collecting, analysing, and communicating information about teaching and learning (SoLAR, 2022). Measurements and collection of data for use in LA are produced by learners during their interactions with online and offline learning environments. MOOCs and SPOCs, predominantly the former, produce vast amounts of educational data on learners' interactions with courses, such as attendance, frequency of access, playback, pauses, quiz scores, and more. The vast amount of complex data produced ticks all the boxes of big data, which is seen as a pioneer in EDM and LA to better understand, analyse, and report on educational data. Analysis and reporting on this data optimises learning and allows decision-making in learning, teaching

and management. LA is enabled by data but not driven by it; instead, it aims to use the data to leverage human decisions through the presentation of meaningful information extracted from the data (Elias, 2011; Kim et al., 2016).

2.4 Self-Regulated Learning

Self-Regulated Learning (SRL) is the self-directive process by which learners transform their mental abilities into academic skills (Zimmerman, 2002). In recent years, SRL has been given increased attention in computer-based learning environments. There are a number of important factors at play here, all of which are in line with broader conversations about the ways in which technology is affecting the teaching and learning processes. More and more pressure is put on educational institutions to educate an increasing number of learners more effectively while maintaining or improving the quality of their education. Given the rapid pace at which the world is changing, it is a challenge to educate learners so that they are prepared for careers and lifestyles in a complicated social and economic environment.

Self-regulation is a set of self-generated thoughts, feelings, and behaviours aimed toward achieving a set of goals. Self-regulated learners constantly monitor their behaviour in terms of their goals. This enhances their self-satisfaction and motivation to improve on their learning methods, resulting in self-regulated learners being more likely to succeed academically and viewing their futures optimistically. Because the development of lifelong learning skills is a primary function of education, self-regulation is crucial, and a vital question to answer is how and what learners need to attain self-regulation. To begin with, self-regulation of learning entails more than a thorough understanding of skills; it also involves self-awareness, self-motivation, and the ability to use that knowledge effectively. Second, according to recent research, self-regulation of learning is not a single personal feature that learners either have or do not have; rather, it entails the selective application of certain processes tailored to each learning task. A learner's level of learning has been found to vary based on the absence or presence of these eight different self-regulatory processes (Schunk and Zimmerman, 1998). Finally, research reveals that self-motivation in self-regulated learners is influenced by a number of underlying beliefs, including perceived efficacy and intrinsic interest. Unfortunately, self-directed learning and practice are sometimes dismissed by learners as fundamentally tedious, repetitious, and mind-numbing; yet interviews with professionals offer an entirely different image of these experiences.

2.4.1 Phases of Self-Regulation

A key component of self-regulation is the personal feedback loop (Zimmerman and Moylan, 2009). The feedback loop is a series of self-regulatory processes that create feedback about learners' performance and are used to adapt to the learner's learning process. According to

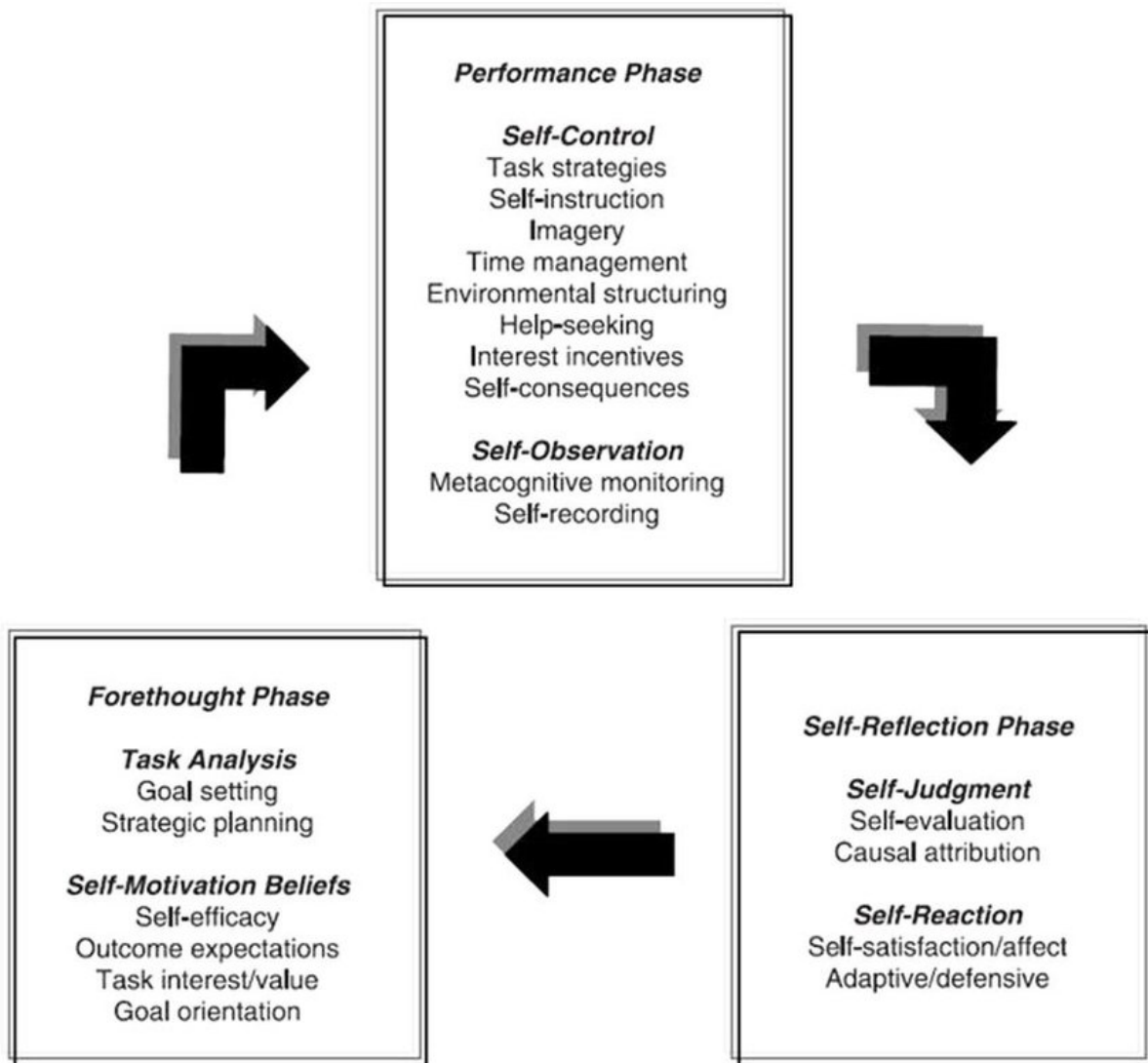


Figure 2.1: Phases of Self-Regulation (Zimmerman and Moylan, 2009)

social learning psychologists, self-regulatory processes are divided into three cyclical phases. Processes and beliefs that occur before learning efforts to influence their preparation and willingness to learn are referred to as *forethought*; processes that occur during learning are referred to as *performance*, and influence learner's concentration and performance; and processes that occur after learning efforts are referred to as *self-reflection* (Zimmerman, 2002). These phases have different functions in the self-regulation of learning and are further divided into what Zimmerman calls *classes*. An overview of the phases, classes, and processes of each class are shown in figure 2.1.

Forethought

The processes of the forethought phase is divided into two classes: *task analysis* and *self-motivation*. Breaking down a maths problem into sequential phases is an example of task analysis, which entails breaking down a learning assignment and its context into a series of

tasks and developing a personal approach to the problem using past knowledge of these tasks. *Goal-setting* and *strategic planning* are two important aspects of task analysis (E. Locke and Latham, 2002). Goal-setting involves defining the desired objectives of the learner, and strategic planning involves defining the steps that will be taken to achieve these goals. Learners can practise effectively by themselves for long periods of time when they can relate their strategic planning to short and long-term goals. Goal-setting serves several purposes in self-regulation and has been found to enhance self-regulation in learners greatly. Locke and Latham (E. Locke and Latham, 2002) found four mechanisms of goal-setting that affect performance.

First and foremost, goals orient the learner's attention and effort towards goal-relevant activities. This influence is both cognitive and behavioural. According to Rothkopf and Billington, learners with specific learning goals paid more attention to and remembered goal-relevant prose passages better than goal-irrelevant passages (Rothkopf and Billington, 1979). Furthermore, Locke and Bryan (E. A. Locke and Bryan, 1969) found that learners who were provided feedback on several performance elements on an automobile-driving activity increased their performance on the dimensions for which they had goals, but not on the other dimensions. Second, goals can be used to motivate learners to give greater effort on tasks. It has been shown (E. A. Locke and Bryan, 1969) that high goals lead to more significant effort in tasks that entail physical effort, repeated performance of cognitive tasks, measurements of subjective effort, and physiological indicators of effort. Third, persistence is influenced by goals. Hard goals extend effort when participants are given control over how much time they spend on a task; however, there is frequently a trade-off in work between time and effort intensity. When faced with challenging goals, it is feasible to work quickly and intensely for short periods or slowly and less intensely for longer periods. It has also been shown that tight deadlines lead to greater effort than loose deadlines. Finally, goals indirectly influence action by causing arousal, discovery, or application of task-relevant knowledge and methods.

Forethought relies on a variety of key sources of self-motivation because it is anticipatory. Goal-setting and strategic planning have been related to each of these sources of motivation; for example, self-efficacy has been found to predict learners' goals and strategic planning by affecting the choices learners make in their use of activities, effort, and persistence (Zimmerman et al., 1992). Outcome expectations, a second key source of self-motivation, are also related to learners' performance. Although attractive results have a well-established positive effect, these expectations are also influenced by self-efficacy beliefs. In the forethought phase, learners' task interest, or value, is the third source of self-motivation. As opposed to the task's intrinsic utility in achieving other goals, this interest or value refers to a person's liking or disliking of a task and influences the learner's choice of learning strategies and achievement goals. The fourth source of self-motivation is learners' goal orientation, which includes their views or attitudes towards the learning purpose. Although notable theorists' research on learners' goal orientations has resulted in different conclusions, most research is in agreement on the function of goal orientation, whether learning or performance-oriented. Finally, the differ-

ence between goal setting and goal orientation should be noted; goal-setting commits learners to achieve a certain academic goal within a specified time, whereas goal orientation does not. Goal setting creates an explicit feedback loop that necessitates self-evaluation at a defined point in time. In contrast, goal orientation is an open-ended commitment to participate in learning or performance activities (Zimmerman and Moylan, 2009).

Performance

Self-control and *self-observation* are the two classes of processes in the performance phase of self-regulation. Self-control strategies used by learners include both task-specific and general strategies. Task strategies refer to the development of systematic procedures for tackling specific components of a task, such as creating steps for calculating the hypotenuse of a right triangle in maths or sorting lists in computer science. Self-control concerns several general strategies (Zimmerman and Moylan, 2009), such as *self-instruction* that refers to explicit or implicit instructions given while performing a task; *imagery*, which is the act of converting written information into visual diagrams and/or flow charts for extracting information using non-verbal visuals; *time management*, which relates to tactics for completing tasks on time, such as creating explicit task goals, task time estimations, and tracking progress towards these goals; *environmental structuring*, an approach to self-control for improving the efficacy of one's surroundings. Another strategy of self-control is asking for help when learning or performing tasks, known as *help-seeking*. Because help is sought from others, help-seeking can appear to the casual observer as the polar opposite of self-control; however, poor achievers are known to be hesitant to seek guidance from others (Newman, 2002), perhaps because they are not aware of whom to ask for help from, what to ask for, or when to ask for it.

Interest enhancement is a strategy aiming to make routine work more interesting by adding game-like features, often referred to as "gamification" (Caponetto et al., 2014), such as competing with other learners on who can complete a task faster or recall more information from a task. Another motivational strategy of self-control is *self-consequences*, which is an approach to self-control that involves the establishment of rewards or punishments for specific actions, such as rewarding oneself for completing tasks on time. The strategies listed are not exhaustive; rather, it illustrates the range of strategies used to enhance learners' self-control. All of these strategies, whether specific or generic, must be adjusted based on the outcomes of learners, which is why self-observation is so important in learners' efforts to self-control their performance. Self-observation can, however, become a daunting task when the information in academic achievement surpasses their mental capacity. This can be avoided if learners learn to track crucial processes selectively, and recording of progress improves self-observation by reducing the amount of information they need to remember and allows them to detect and evaluate tiny changes in performance over time.

Self-Reflection

The self-reflection phase is the last phase of the self-regulation feedback loop. It is divided into two classes: *self-judgement* and *self-reaction*. Comparing one's performance to a benchmark, *self-evaluation*, is a common way of performing self-judgement, usually using one of three categories of evaluative standards defined by Bandura in 1986 (Bandura, 1986); comparison against the performance of others, against previous performance levels, and mastery of a skill. Learners should select performance goals with discretion, as higher but unrealistic goals ultimately undermine the motivation to keep striving when the feedback of self-evaluation is unfavourable. The benchmark that learners select to judge themselves during the self-reflection phase will be based on the goals they establish in the forethought phase. It is worth noting that a learner's choice of benchmark might have a significant impact on their perceived outcomes, therefore, their subsequent motivation. For example, using one's performance as a benchmark commits the learner to self-improvement rather than striving to beat the performance of other learners who may have started with an advantage. Causal attributions - "beliefs about the causal implications of personal outcomes, such as one's fixed ability, effort, and use of strategies" (Zimmerman and Moylan, 2009)- are the second type of self-judgement significant in understanding self-regulation cycles. Several researchers have voiced worry that certain sorts of performance attributions can easily reduce self-motivation, such as attributing errors to uncontrollable factors like lack of talent or ability. On the other hand, attributing errors to controllable factors like lack of effort or using a specific strategy can be a positive way to boost self-motivation.

Self-satisfaction and *adaptive/defensive decisions* are two types of self-reaction that make up the second important class of the self-reflection phase. The cognitive and affective responses to one's self-judgments are defined as self-satisfaction. Learners favour activities and strategies that previously resulted in satisfactory performance and tend to steer clear of activities that resulted in poor performance. Adaptive and defensive decisions encourage and prevent learners from continuing their use of strategies. With adaptive decisions, learners adjust their strategies to improve motivation to engage in additional learning cycles, while defensive decisions prevent further learning efforts to avoid future disappointment. It is important to note that both types of learners' self-reactions are based on self-judgments during the self-reflection phase. Positive self-evaluations of one's performance and attributions to controllable factors, for example, will lead to higher self-satisfaction and sustained adaptive learning efforts. These self-reactions have a cyclical effect on the forethought phase during subsequent endeavours to achieve satisfactory performance. Positive self-satisfaction leads to higher self-motivation, self-efficacy, and a greater intrinsic interest in the tasks. Therefore, self-regulatory processes can become self-sustaining due to their cyclical effects in which strategies and beliefs in each phase produce inertia that can either promote or inhibit learning efforts in later phases.

2.4.2 Learning Analytics in Self-Regulated Learning

There are many important issues to consider when determining what LA may be able to offer in the way of assistance to encourage the growth of SRL. The requirement to properly notice when essential phases of SRL are occurring, determine whether or not they are developing appropriately, and know-how to remediate the learner if they are not developing appropriately is one of the most crucial issues associated with this problem. According to Winne, using trace data to infer whether or not learners are engaging in SRL is "mildly imperfect and slightly unreliable." (Winne et al., 2017). However, Winne also argues that when analysed with care, these data have the potential to provide essential indicators of features of SRL. This suggestion stands in contrast to "numerous arguments that trace data has limited utility in inferring high-level cognitive processes, such as those involved in SRL." (Winne et al., 2017). Therefore, this would seem to indicate that an approach based on behavioural data might need to be combined with other indicators and that its interpretation might need to be done very carefully in order to support SRL. There has been significant development on two fronts, which may lay the groundwork for the practical application of LA to support SRL in the future. The first of these is the development of new instruments and methods for synthesising the data obtained from a variety of instruments in order to infer when more complex cognitive processing and emotional reactions are taking place. The second development is the increased collaboration between design and LA, which makes it possible to make sense of data in a manner that is both better organised and contextualised.

As soon as SRL processes are discovered in online learning environments, the question of what to do with the information arises. There are already some exciting options for utilising LA that support SRL. Timmers et al. (2015) drew from behavioural trace data that was collected as learners worked on problem-solving exercises in an online learning environment and showed that feedback given to the learners based on their learning tactics could help them improve their ability to self-evaluate their progress when they later worked on other problem-solving exercises (Timmers et al., 2015). Pardo (2017) presents a model for providing feedback that is driven by data, along the lines of Timmers et al.'s experiment. The real-time feedback given to learners in this model is designed to encourage increased strategies, tactics, and regulation in the direction of the pedagogical goals that they are aiming to achieve. The purpose of these interventions is to convince the learners to pause what they are doing, take notice of how far they have come, and adjust their approach in some way if deemed necessary (Pardo, 2017). These methods, by definition, focus on learners' self-regulated learning as a means of enhancing the development of their learning and, as a result, the learning outcomes of those learners.

2.5 Summary

This chapter presents relevant theories and methods for this research. LA is central to the development of the dashboard, and key characteristics of dashboard design have also been presented in this chapter, along with guidance on learner feedback in dashboards. Self-regulation and LA's role in SRL are explained, laying the foundations for the discussion of this research later. Finally, issues facing the area of LA and SRL have been presented.

Chapter 3

Methodology

This chapter presents the methodologies used in this research. Design Science research, desk research, Agile development, and the evaluation methods are described.

3.1 Design Science

Design Science (DS) is a research methodology concerned with the design and investigation of artefacts in context and aims to produce workable and practical artefacts for problems with potential for improvement (Wieringa, 2014). The concept of an artefact should, however, be considered broadly, as it can include software and hardware components, methods, algorithms, and conceptual structures. Artefacts of DS are not necessarily aimed at *solving* the problem, but rather to improve the interaction with the problem through the medium of an artefact. Therefore, researchers in DS should not only study the artefact or the context alone but rather the interaction of artefacts and their contexts to produce knowledge about the problem and its potential solutions.

DS is rooted in the sciences of the artificial and engineering, and plays an important role in the Information Systems (IS) literature (Simon, 1996). However, an important duality must be addressed in order to truly comprehend and appreciate DS as an IS research paradigm. Design is not only a product but also a set of processes that describes the world as it is acted upon (Hevner et al., 2004). The design process is a collection of actions that results in a unique design artefact, which is then evaluated to reveal further knowledge of the problem. This allows both the product's quality and the design process to be improved. Before the final design artefact is developed, the build and evaluate feedback loop is usually repeated several times. Designing effective artefacts is, therefore, a complex task due to the necessity for creative breakthroughs in domains where existing theories frequently are insufficient to provide the necessary insights.

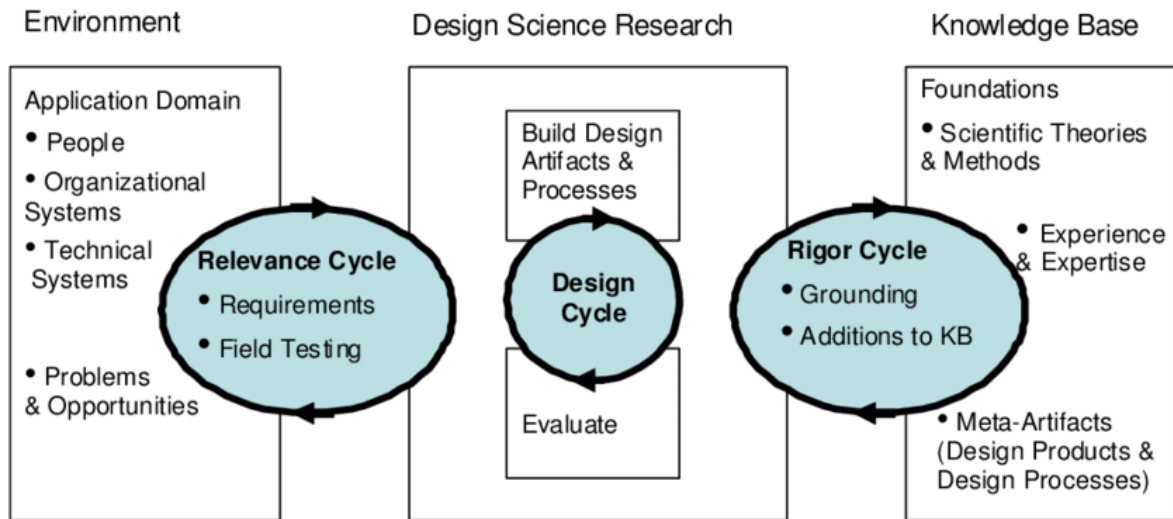


Figure 3.1: Research cycles of Design Science (Hevner, 2007)

3.1.1 Design Science Research Cycles

Alan Hevner argues for the existence of three DS research cycles in his commentary on Juhani Livari's essay (Livari, 2007) on the information system's role in DS (Hevner, 2007). DS is clearly distinguished from other research paradigms by the recognition of these three research cycles. Figure 3.1 illustrates the three research cycles.

Relevance Cycle

The *relevance cycle* initiates research with a context that not only provides the problem being addressed, but also establishes the ultimate criteria for the research's final evaluation. This cycle is concerned with whether or not the artefact can, in fact, improve the environment and, if so, how it can be evaluated. Wieringa further refines this concept in what he calls the "social context" and notes that this context contains the stakeholders of the research, such as "possible users, operators, ... of the artifact to be designed." (Wieringa, 2014).

Rigour Cycle

The *rigour cycle* provides past knowledge to the research project through thorough research and application of relevant theories and methods in the design, construction and evaluation of the artefact to ensure innovation in the project. However, due to the nature of DS, all design research cannot be grounded in descriptive theories (Hevner, 2007). As such, several different sources of ideas and theories should be used as the groundwork for the conducted research, with additional sources of creative insights.

Design Cycle

The *design cycle* is the heart of the DS research, bridging the activities in the relevance cycle with the knowledge from the rigour cycle. In this cycle, the researcher iterates rapidly between the construction of the artefact, its evaluation, and subsequent iterations to further refine the produced artefact. According to Simon (Simon, 1996), this cycle begins with the production of design alternatives, which are then evaluated against the criteria established in the relevance cycle until a satisfactory design is achieved.

3.1.2 Guidelines for Design Science Research

DS research in Information Systems (IS) addresses problems that are characterised by having volatile constraints and requirements due to the nature of the context in which research is carried out. Furthermore, research in this field has a critical dependence on human social and cognitive abilities to produce effective solutions. As a result of these problems, Alan Hevner et al. (Hevner et al., 2004) present a set of adaptive and process-oriented guidelines that should guide any DS research in IS. See table 3.1.

Table 3.1: Design Science research guidelines

Guideline	Description
Design as an Artifact	Design-science research must produce a viable artifact in the form of a construct, a model, a method, or an instantiation.
Problem Relevance	The objective of design-science research is to develop technology-based solutions to important and relevant business problems.
Design Evaluation	The utility, quality, and efficacy of a design artifact must be rigorously demonstrated via well-executed evaluation methods.
Research Contributions	Effective design-science research must provide clear and verifiable contributions in the areas of the design artifact, design foundations, and/or design methodologies.
Research Rigor	Design-science research relies upon the application of rigorous methods in both the construction and evaluation of the design artifact.
Design as a Search Process	The search for an effective artifact requires utilizing available means to reach desired ends while satisfying laws in the problem environment.
Communication of Research	Design-science research must be presented effectively both to technology-oriented as well as management-oriented audiences.

Design as an Artefact

By definition, DS research in IS is concerned with the production of a workable and practical artefact to solve a defined problem in a given context. The produced artefacts are not neces-

sarily full-grown ISs, but rather a set of ideas and products that, through analysis and design, can be efficiently accomplished in their given context. Instantiation of the artefact serves to demonstrate both the design process and the designed product's feasibility. Furthermore, it provides "proof by construction" that the artefact can, in fact, solve the defined problem.

Problem Relevance

The objective of any DS research in IS is to enable the design and production of a workable artefact through acquiring knowledge and understanding of the problem it aims to solve. The problem must be understood in order to best prepare the researcher to solve the problem and to ensure the relevance of the problem in the context, which can only be achieved by extensive research into both the problem and the problem domain.

Design Evaluation

In order to prove and validate that an artefact works in its context, researchers need to rigorously demonstrate the utility and quality of the designed artefact. Evaluation is crucial to demonstrate this and also provide valuable feedback in the design cycle that will allow further refinement of the artefact. Evaluation needs to be based on the requirements found in the relevance cycle and must be done in the context for which the artefact is meant to be used. A designed artefact is only complete when it satisfies the requirements and constraints it was meant to solve (Hevner et al., 2004).

Research Contributions

More often than not, the artefact itself is the contribution of DS research. Other contributions include foundations, such as evaluated constructs or methods that improve the existing knowledge in DS, and methodologies, such as measures and evaluation criteria. In any DS research project, at least one of these contributions must be present, solving a previously unsolved issue.

Research Rigour

Rigour in DS research is concerned with how research is conducted and requires both the production and evaluation of the produced artefact to be implemented by rigorous methods. Hevner et al. (2004), along with IS researchers, argue that it is necessary for all IS research to be relevant and rigorous. Typically, assertions regarding the produced artefact are based on certain performance criteria, which the researcher must regularly review to verify that the criteria are adequate. Furthermore, while assessing how well an artefact works, it must be evaluated within the proper context with stakeholders of the artefact.

Design as a Search Process

"Design is essentially a search process to discover an effective solution to a problem." (Hevner et al., 2004). The solution to a problem can be found within the set of all possible designs that satisfy the ultimate criteria of the artefact, and it is here the researcher has to search for the proper solution. However, it may not be possible to explicitly determine what the solutions look like, and as such, DS research is about the search for a satisfactory solution to the given problem. That is, the goal of DS research is to produce an artefact that works well enough for the problem it tries to solve.

Communication of Research

One of the main issues with the communication of DS research results is the fact that the research must be communicated not only to technology-oriented audiences but also to the end-users that the artefact is aimed at. Technology-oriented audiences need enough detail about the implementation to enable them to reproduce the artefact within a relevant context and should enable practitioners to reap the benefits of the research conducted. End users, however, need enough detail to determine if the artefact can be used effectively within their specific context.

3.2 Desk Research

Secondary research, often known as desk research, refers to the process of reviewing the work that has been done by other researchers. There is no data collection involved; instead, the researcher is responsible for analysing the findings of prior research in order to acquire a comprehensive understanding of the research areas (Travis, 2016). Desk research is often used in order to answer the research questions of research with better statistical significance due to the support of prior research. Furthermore, it can help to identify when a research question is answered or when new knowledge is found.

In this research, desk research is used to gain a comprehensive knowledge of LA and SRL and to answer the research questions with support from prior research.

3.3 Agile Development

In the 1990s, it was believed that software development was in a crisis, "The Software Crisis", as many referred to it as. According to the frequently quoted "CHAOS report", approximately one-third of software projects were terminated because they went over budget, were late, and did not fulfil the requirements (The Standish Group International, 1994). In order to put software development under control, large corporations developed elaborate processes that outlined precisely how software was to be developed, and everything was closely regulated to

eliminate the possibility of error (In principle, at least) (Shore and Warden, 2021). The resulting development methodologies came to be known as "waterfall development" because of the fact that the software was developed in a series of phases, each of which was performed after the previous phase was completed. Several people didn't think this was a great way to work, so they created lightweight methods for developing software, in contrast to the heavyweight methods used by large corporations. These methods attracted the attention of programmers by the late '90s, and seventeen leading figures of lightweight methodologies met in 2001 to discuss the problem. The result was the Agile Alliance and the Agile Manifesto.

Manifesto for Agile Software Development

We are uncovering better ways of developing software by doing it and helping others do it. Through this work we have come to value:

- **Individuals and interactions** over process and tools
- **Working software** over comprehensive documentation
- **Customer collaboration** over contract negotiation
- **Responding to change** over following a plan

That is, while there is value in the items on the right, we value the items of the left more.

Kent Beck

Mike Beedle

Arie von Bennekum

Alistair Cockburn

Ward Cunningham

Martin Fowler

James Grenning

Jim Highsmith

Andrew Hunt

Ron Jeffries

Jon Kern

Brian Marick

Robert C. Martin

Steve Mellor

Ken Schwaber

Jeff Sutherland

Dave Thomas

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Figure 3.2: Agile Manifesto

3.3.1 Agile Manifesto

There has never been a unified Agile method, and there never will be. There are three components that make up what Agile is: the name, the values, and the principles. It is not something that can be done, because it is a way of thinking. You can only *be* Agile, you cannot *use* or *do* Agile. Ultimately, the Agile Manifesto provides values and principles that should guide the software development process (Shore and Warden, 2021). The Agile Manifesto can be seen in figure 3.2.

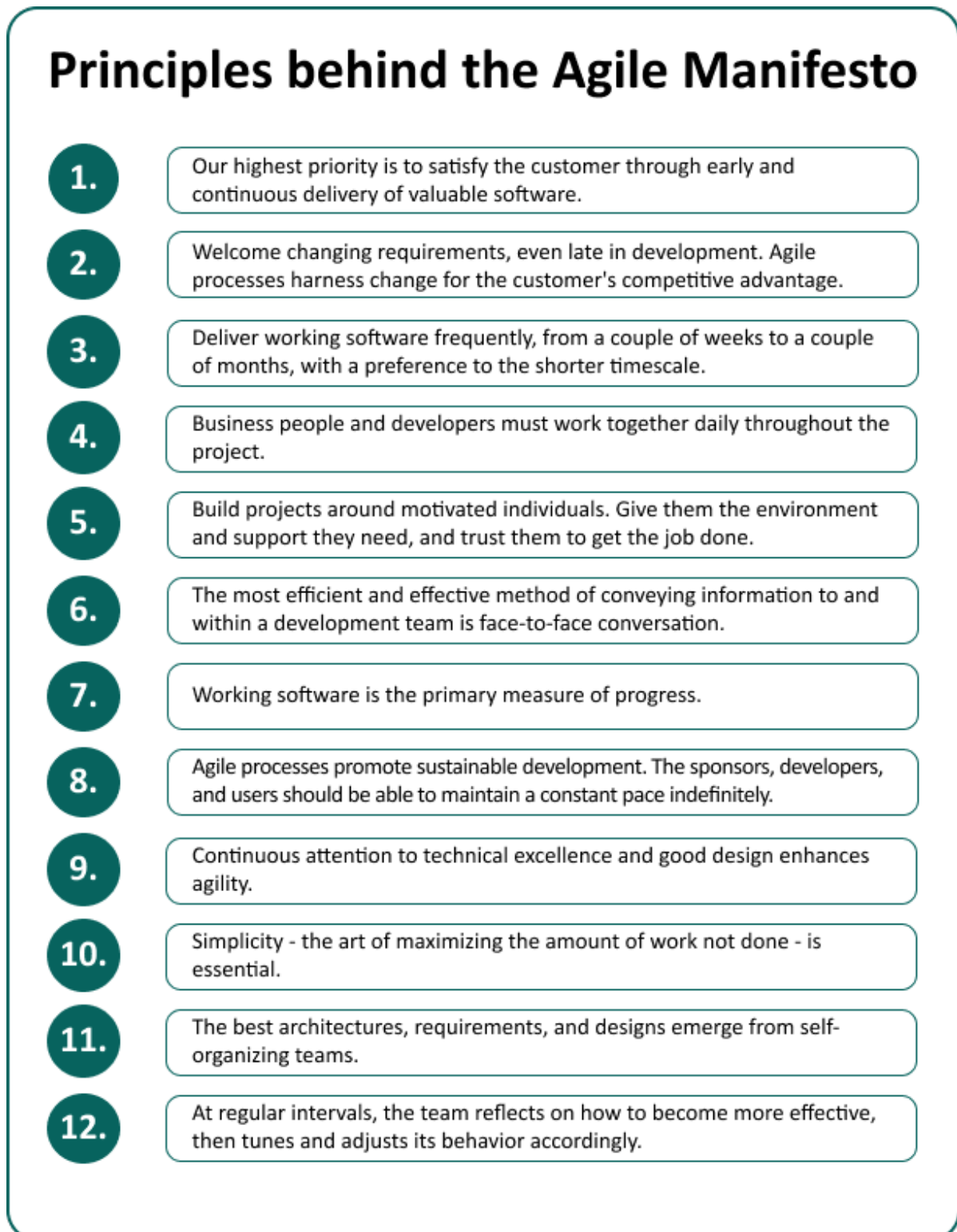


Figure 3.3: Agile Principles

3.3.2 Agile Principles

The Agile Alliance has created a collection of 12 fundamental principles as a complement to the Agile Manifesto. These principles offer direction and a more in-depth explanation of Agile software development in addition to the Agile Manifesto. The principles can be seen in figure 3.3. The collaborative effort of self-organised teams is at the heart of agile processes, which sees both requirements and solutions evolving over time. According to the manifesto's first principle, "Our highest priority is to satisfy the customer through early and continuous delivery of valuable software." (Alliance, 2001). This is essentially the major focus of Agile development, which places emphasis on generating a Minimum Viable Product (MVP) that is improved upon through iteration before anything is considered complete. Feedback from consumers and other stakeholders is collected and incorporated continuously, providing the customer with a competitive advantage in an environment that is constantly shifting (Paradigm, 2022). Scrum and Kanban are the two most popular Agile frameworks. A prioritised set of needs and requirements that will be delivered by the team is the essential component of the Scrum framework. Iterations in Scrum are referred to as "sprints", and they are often quite short, with a significant emphasis placed on creating an MVP. Kanban, on the other hand, is a technique for organising knowledge work that places a priority on "just-in-time" delivery while at the same time ensuring that team members are not overworked. Kanban is frequently used in tandem with a variety of other approaches (Cradle et al., 2014).

3.3.3 SCRUM

The SCRUM framework is heuristic, which means that it is built on ongoing learning and the ability to adapt to changing conditions. It recognises the fact that the team will learn new things as they gain experience and that they do not know everything at the start of a project. SCRUM is designed to facilitate the natural adaptation of teams to shifting conditions and evolving user requirements. With re-prioritisation integrated into the process and short release cycles, teams will be able to continuously learn and develop (Atlassian, 2022). There are three artefacts in SCRUM that make up the framework: the Product Backlog, the Sprint Backlog, and the Sprint. The Product Backlog is the list of items that the team needs to develop. The Sprint Backlog is the list of items that the team needs to develop during the current Sprint. The Sprint is the period of time during which the team works towards the Sprint Backlog. Furthermore, SCRUM is also composed of some key ceremonies: Sprint Planning, Stand-up, and Retrospective. Sprint Planning is the process of creating the Sprint Backlog by prioritising the tasks in the Product Backlog. The Stand-Up is a (usually) daily meeting where team members answer three questions: what did we do yesterday, what are we doing today, and what are the obstacles? This meeting helps the team to understand the progress of the Sprint and to identify any problems that may be preventing the team from meeting its Sprint Goal.

The Retrospective is the process of gathering feedback from the team and the Product Owner in order to learn from mistakes, improve processes, and keep procedures going as planned.

Because of its flexibility and heuristic approach to resolving complex and unpredictable problems, SCRUM was selected as the framework for the development process of this project. The application of the SCRUM framework requires the participation of more than one person; however, given that this project was carried out individually, the principles of SCRUM were simply used as a point of reference for the activities that comprised the development process. Fortuitously, fantastic folks from Bouvet ASA were able to provide assistance with the SCRUM ceremonies, occasionally participating in Stand-Ups, Retrospectives, and Sprint Planning.

3.4 Evaluation

Evaluation is the act of gauging how well a product or service performs in relation to a "particular expectation, objective or *need" (Hirschheim and Smithson, 1999). In this research, the evaluation process is focused on the usability of the dashboard, the learners' perceived value of the information presented, and how it influences their motivation and performance. The evaluation methods used in this research are covered in the following subsections.

3.4.1 Quick and Dirty

A frequently used approach to evaluating the usability of a system is a "quick and dirty" evaluation, in which designers informally gather input from users or consultants to validate that their ideas are in line with the requirements of users and are approved by those users. Evaluations that are "quick and dirty" can be performed at any time, and the focus is on providing input as quickly as possible rather than thoroughly documenting the findings. Receiving feedback of this nature is a vital component of designing a successful system (Preece et al., 2002). In this research, "quick and dirty" evaluations are used throughout the design phase of the dashboard in order to gauge the usability of the dashboard and learners' perception of the information presented.

3.4.2 Case Study

A case study is a method of research that is used to develop an in-depth, multifaceted understanding of a complicated topic in its real-life context. It is a tried-and-true method of research that has found widespread use across a wide range of academic fields, most notably in the social sciences. A case study can be characterised in a variety of ways; nevertheless, the essential component is the requirement to investigate an occurrence or phenomenon in great detail and in the context in which it occurs naturally (Crowe et al., 2011). In this research, a case study is

used to evaluate the usability of the dashboard and learners' perception of the information presented on the dashboard. The case study is conducted in cooperation with OsloMet university, where learners at the course "VUNG6000" are given access to the dashboard in the last two weeks of the course before participating in the final evaluation consisting of semi-structured interviews and a questionnaire. VUNG6000 is a further education course for nurses, covering "Sexual and Reproductive Health and Rights". The course is further specialised in "Young Sexuality, Self-Determination and Diversity" (OsloMet, 2020).

3.4.3 Semi-Structured Interviews

A typical practice to acquire qualitative data is through oral questions and responses in interviews. Interviews are useful for collecting participants' feelings, thoughts, and beliefs (Institute, 2022). Interviewing participants qualitatively can be helpful when evaluating programs that are aimed toward tailored outcomes, studying individual disparities between the experiences and outcomes of participants, and gaining knowledge of what a program means to the people who use it (Sewell, 1999).

In order to collect data about the dashboard, a technique known as semi-structured interviews is used. It involves posing questions within the confines of a specific thematic framework. However, neither the order nor the wording of the questions is fixed (George, 2022). Instead, the interviewer is given the freedom to direct the flow of the conversation between them and the interviewee while still being organised in such a way as to ensure that interviewees discuss the same set of questions. The interviews were conducted after the learners had used the dashboard for the last two weeks of the course.

3.4.4 Questionnaire

The provision of information that can be quantified to provide answers to questions is the primary function of quantitative data. Quantitative data can be gathered in a variety of ways including surveys, questionnaires, observation, or the collection of clinical data. For the purposes of evaluating learners' perceived value of the information presented to them, a questionnaire where respondents score several dashboard features on a scale of 1 (very poor) to 10 (very good) is used. The questionnaire is administered after the semi-structured interview is conducted and will be carried out via Zoom.

3.4.5 Problems

While the types of evaluations discussed above are helpful in gauging the usability of the dashboard and the learners' perception of the information presented, a few problems related to these evaluations should be noted. Firstly, the adaptability of semi-structured interviews

often work against the validity of the results. Depending on how far the interviewer deviates from the list of questions prepared beforehand, comparing the participants' responses can be a difficult task. Secondly, the fact that semi-structured interviews are open-ended means that it is easy to fall into the trap of posing leading questions, which might influence the responses given. On the other hand, respondents may also try to give you the answers they think you want to hear, which could result in social desirability bias (George, 2022). Finally, as must be considered in any type of evaluation, is the possibility that the wording of questions or certain characteristics of the interviewer is producing a response bias (Institute, 2022).

3.5 Summary

This chapter has introduced the methodologies for this research, most notably Design Science, which have been used to guide the research. The Agile development framework SCRUM has been presented, along with the evaluation methods used to evaluate the usability and impact of the dashboard. Lastly, the desk research that led to the background of this thesis has also been presented.

Chapter 4

eduGraph

This chapter presents the eduGraph dashboard, which was constructed throughout the course of this research. Figure 4.1 illustrates the eduGraph logo. The goal of this research was to design a dashboard that the learners could use to monitor their progress on a semi real-time basis (updated daily), that would provide quick access to the learner's activity, allow the learner to visually explore their progress, and provide individualised feedback to support the learner's ability to engage in SRL based on their activity and their progress.

The logo for eduGraph, featuring the text "eduGraph" in a teal, sans-serif font. The "G" is significantly larger than the other letters, and the "u" is lowercase. The "e" is lowercase, and the "d" is lowercase. The "r" is lowercase, and the "a" is lowercase. The "p" is lowercase, and the "h" is lowercase.

Figure 4.1: eduGraph Logo

4.1 Project Timeline

In this section, a timeline is provided to give the reader a better understanding of how the work was performed throughout seven phases. The timeline is presented in figure 4.2.

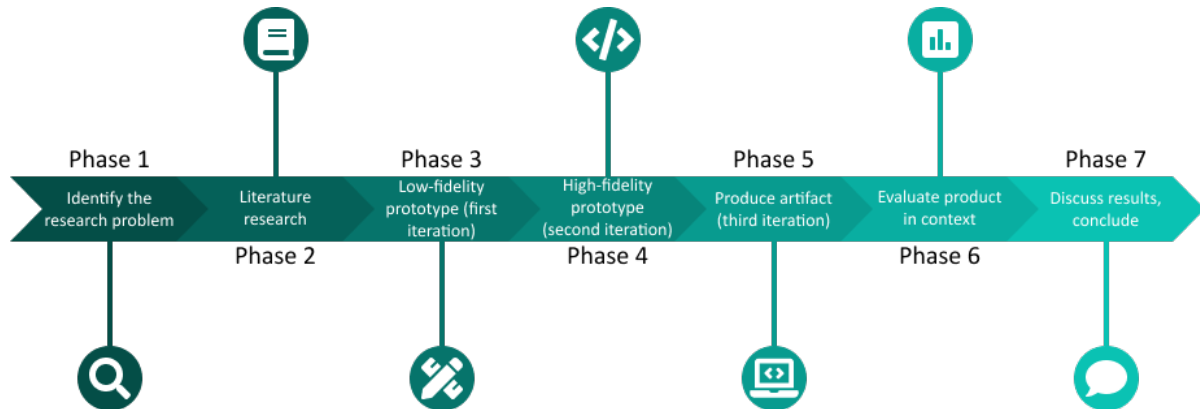


Figure 4.2: Phases of the project

Phase 1 In the early stages, establishing the nature of the problem to be investigated was the primary focus. As noted in section 2.3.2 (Existing LADs), the lack of LADs that are specifically targeted at learners presents an opportunity to investigate further the effects of LADs on learners' performance and motivation, as well as to investigate the potential of LADs to improve their learning experience. In addition, the research questions were formulated in a way that allowed the thesis to build upon the existing knowledge of LA and to investigate the potential for SRL to enhance the learning experience for learners using LADs.

Phase 2 In the second phase, methodologies that would be used to address the research questions were determined. In order to identify the methodology, extensive research into relevant literature was carried out. It was necessary to have a comprehensive knowledge of both the field of LA and the theoretical area of SRL in order to decide the most effective way to respond to the research questions and to evaluate the potential of LADs to improve the learning experience for learners.

Phase 3 The development of a low-fidelity prototype of the LAD was carried out in the third phase. In order to identify the core layout of the dashboard, "quick and dirty" evaluations with learners were carried out using the LAD prototype. The prototype was rapidly iterated upon as feedback was received from learners before settling on a final design for the dashboard.

Phase 4 The prototype from phase three underwent additional iterations of polishing during the fourth phase of the project in order to improve the user interface and the usability of the dashboard. A high-fidelity prototype was created using Figma. The prototype was made

available to learners in this phase, and the design of the dashboard was further refined through a number of iterations of testing using the prototype.

Phase 5 Feedback from learners from the third and fourth phases was utilised in the fifth phase, which culminated in the creation of the dashboard. The dashboard underwent continuous development, testing, and incremental improvements until it was ready for distribution to OsloMet learners.

Phase 6 Evaluation of the dashboard was carried out in the sixth phase. Learners were granted access to the dashboard, and a subset of those learners participated in an interview to discuss the dashboard's influence on their overall learning experience, as well as their level of motivation.

Phase 7 The seventh and last phase includes a discussion of the findings obtained from the research and evaluation. The findings are put to use in the process of developing a strategy for the continuation of the project. Future expectations and directions are also discussed in this phase.

4.2 eduGraph Development

This section provides an overview of the eduGraph development process.

4.2.1 Tools and Technologies

During the course of this research, a number of different tools and technologies connected to the creation and deployment of eduGraph were utilised. In the following part, an overview is given.

Project Management

The management of the project was simplified by the utilisation of a number of different tools, which will be discussed in detail in the following paragraphs.

Version Control A mechanism that enables the tracking and management of changes made to the software is known as version control or source control. A Version Control System (VCS) monitors any and all code modifications and stores the history of those changes in a location referred to as a repository. Git, which is a VCS, is free, open-source software that was used to maintain the repository for this project. Git is currently one of the most widely used VCSs, thanks to its branching, merging, and traceability capabilities. GitHub, a free hosting site for VCSs that employ the Git protocol, was utilised so that the code could be

safely stored and managed. GitHub provides all of Git's features in addition to its own, which include bug tracking, code review, wikis, and continuous integration. These are all instruments that simplify the management of the project, which in turn makes it easier to maintain its consistency and dependability.

Task Management The concept of Sprint tasks and a Sprint and Product Backlog are some of the essential aspects of the SCRUM framework. Trello is a free Kanban-style board that can be accessed on the Internet and provides an easy way to organise and manage tasks. Additionally, it enables the establishment of checklists, labels, and priorities, in addition to the ability to assign tasks to different categories. In order to keep track of everything that needed to be done in this project, its importance, issues that needed to be resolved, and bugs that needed to be fixed, Trello was utilised as a task management tool.

Design and Prototyping Tools

Prototyping is an experimental process in which designers create tangible representations of their ideas, which might range from paper to digital. The prototyping process can occur anywhere. Designers construct prototypes with varying degrees of fidelity for the purposes of capturing design concepts and validating them with users. Prototypes can be used to refine and validate designs, allowing organisations to test and evaluate products before they are implemented (I. D. Foundation, 2018). One of the benefits of using prototypes is not immediately apparent, but it is of almost crucial importance; the risks of a project with a completed prototyping phase are much lower than those of a project with no prototyping. Prototypes have a direct impact on the most vital aspects of a project, including resources, schedule, and budget. After a prototyping phase is completed, the majority of hidden flaws are revealed, and functional gaps are identified, allowing for better planning of the development process. Furthermore, prototypes are often used as the project specification, aiding developers in creating a more robust and efficient project. Having a prototype facilitates the understanding of each team member's responsibilities and affords them the option to estimate development timelines and costs more realistically and with greater precision (Mishra, 2019).

Figma Figma is a web-based vector graphics editor and prototyping tool released in 2016 (W. Foundation, 2022). It is a free cloud-based design tool which allows designers to create designs in a collaborative environment. Furthermore, since it is a cloud-based tool, Figma works on any operating system that can run a web browser. This makes it an excellent tool for prototyping where designers can collaborate just as they would with, e.g. Google Docs, reducing design drift - incorrectly interpreting or deviating from the design specification. Finally, prototyping in Figma is straightforward and intuitive, removing the need for designers to spend time learning how to use the tool, a valuable characteristic of a prototyping tool (Kopf, 2018).

API Development Tools

An Application Programming Interface (API) is a collection of specifications and protocols for building and integrating application software. It gives businesses the ability to share the data and functionality of their applications with external developers, business partners, and internal departments. The use of a specified interface enables products and services to communicate with one another and take advantage of the data and functionality offered by one another. One of the key characteristics of APIs is that they are designed to abstract away the underlying implementation details, allowing developers to focus on the functionality and data that they need to build their application; they are not required to know how the API itself is built (Education, 2020; Hat, 2017). APIs originated in the earliest days of computing, well before the advent of the personal computer. At the beginning of the twenty-first century, APIs had become an essential tool for the remote integration of data (Hat, 2017).

Web APIs utilise HyperText Transfer Protocol (HTTP) or HyperText Transfer Protocol Secure (HTTPS) to communicate and define the structure of response messages with external web servers, services, and web applications. Most web APIs respond with either an Extensible Markup Language (XML) or JavaScript Object Notation (JSON) file, or both because they convey structured data in a manner that is simple to manipulate by other applications. Today there are three specifications that are commonly used for the transmission of data through web APIs:

- **Simple Object Access Protocol (SOAP):** SOAP was established as a protocol specification in 2001 to standardise information exchange in response to the proliferation of web APIs (W3Schools, 2022). SOAP is an extensible and style-independent protocol, allowing developers to design SOAP-based APIs in a variety of ways and add their own customised functionality with relative ease. In contrast to the RESTful specification, SOAP is a highly structured, carefully managed, and well-defined protocol (Bigelow, 2021).
- **Remote Procedure Call (RPC):** RPC is a protocol that offers the operating system's high-level communications paradigm. It provides a logical client-to-server communications mechanism created to support network applications; however, it is just as effective for communication between processes running on the same machine.
- **Representational State Transfer (REST):** REST differs from the other two in that it is not a protocol but an architectural style. Therefore, there are no specific standards for REST-based APIs (RESTful APIs). Instead, APIs are RESTful if they comply with Fielding's six guiding constraints for RESTful APIs (Fielding, 2000).

OpenAPI Specification (OAS) Even though RESTful APIs do not have an official specification, efforts have been made to make the development and documentation of RESTful APIs

easier and standardised. OpenAPI is a JSON-based, open format specification for describing APIs. The OAS offers a standard, language-agnostic interface to RESTful APIs that enables both humans and machines to discover and comprehend the capabilities of a service without access to source code, documentation, or network traffic inspection (Software, 2020). When APIs are appropriately defined using the OAS, consumers can comprehend and interact with the remote service with minimum implementation logic. OAS is maintained by the OpenAPI Initiative (OAI), established in 2016 by a consortium of industry professionals who saw the need for standardising how APIs are described and documented. The OAI is responsible for developing, promoting, and enhancing a vendor-neutral, free, and open format for RESTful APIs. Initially, the OAS was based on the Swagger Specification by SmartBear but has since been donated to the OAI (Initiative, 2022). The API specification described later in this document is based on the OAS.

Swagger Swagger began as a simple, open-source specification for developing RESTful APIs in 2010. It is a collection of open-source, free, and commercially available technologies such as the Swagger UI, Swagger Editor, and Swagger Codegen that enable anyone to create APIs (Software, 2021). Swagger tools were used to create the specification for the API described later in this document.

Backend Tools

A number of different tools and frameworks were utilised in the process of developing the backend for this project. The following paragraphs cover the most essential tools and frameworks that were used.

C#, pronounced C Sharp, is a general-purpose programming language that offers a modern, object-oriented, and type-safe specification. C# applications execute on .NET, a virtual execution system known as the Common Language Runtime (CLR), and a collection of class libraries. The CLR is Microsoft's implementation of the international standard Common Language Interface (CLI). Several properties of C# make it straightforward to learn. It is a high-level language that is easy to understand and abstracts away many of the most challenging programming tasks so that the programmer does not have to worry about them. The user is, for example, relieved of responsibilities for memory management because of .NET's garbage collection scheme. Additionally, due to the fact that it is a statically typed language, code is validated before it is compiled. C# has quickly become one of the most popular programming languages since its introduction in 2000 due to its robust and flexible features, as well as its comprehensive and trustworthy documentation. It is currently the fourth most popular programming language, with approximately 30 % of all developers making frequent use of it (StackOverflow, 2022). Together with the fact that it is in high demand as a programming language in Norway and that I am currently employed as a C# developer, these characteris-

tics make C# a natural choice for the backend of this project. Furthermore, it allows for rapid development by abstracting away the complexity of the underlying platform and allowing for actions such as HTTP requests and responses to be handled by the framework.

Several packages and frameworks were used to develop the backend, some of which are listed below:

- **ASP.NET Core:** ASP.NET Core is a .NET Core library that provides a high-level, object-oriented programming interface to the .NET Framework. It is a portable, open-source implementation of the .NET Framework and is designed to be used to build web apps and services.
- **NuGet:** NuGet is a package manager for .NET Core. It is used to install and manage .NET Core libraries.
- **Cryptography:** The cryptography library is used to hash passwords.
- **JWT:** JWT is a library for creating and validating JSON Web Tokens, which are used to authenticate users.
- **HTTP:** The HTTP library is used to handle HTTP requests and responses.

Visual Studio Visual Studio is an Integrated Development Environment (IDE) created and maintained by Microsoft. It offers functionality such as code completion, code analysis, and code-formatting, as well as several tools and functionalities for building and debugging applications, such as unit testing, debugging, profiling, integrated version control, and integration with Microsoft's own cloud service, Azure. It is arguably the best IDE for C# developers and was chosen because of its powerful features described above.

Frontend Tools

A number of different tools and frameworks were utilised in the process of developing the frontend for eduGraph. The following paragraphs cover the most essential tools and frameworks that were used.

React.js As the JavaScript framework for the frontend, it was decided to use React.js. There is a vast selection of frontend frameworks available; nevertheless, "the golden trio" consisting of React, Angular, and Vue are the most widely used frameworks. React was selected because of its lightweight nature in comparison to Angular, its primary competitor, and because of its simplicity in comparison to Vue. In addition, because React is the framework with which I have the most significant amount of experience, selecting it as the frontend framework was a decision that came about naturally. React is built on the concept of components, which are reusable pieces of code, and enables the development of user interfaces that are interactive.

Because of the mass adoption of React, developers have access to a broad selection of tools and projects that are useful when developing web applications.

Bootstrap Bootstrap is a Cascading Style Sheets (CSS) framework that allows developers to create web applications that are responsive and mobile-friendly. It is a massive compilation of reusable pieces of code written in HyperText Markup Language (HTML), CSS, and JavaScript. It enable developers and designers to build fully functional websites rapidly. Bootstrap was selected as the CSS framework because its documentation is clear, well-written, and describes and explains everything in great depth. The usage of the framework is made more accessible by the inclusion of code samples within the documentation for each individual component. In addition to this, it provides a high level of customizability, which makes the process of putting the frontend design of this project into action more straightforward than would be possible without the use of a framework. In addition to Bootstrap, Reactstrap is also used for creating a responsive web application, a React component library that makes use of the Bootstrap framework.

ReCharts Displaying data is made easier with the help of a number of pre-built components that come with ReCharts. These include graphs, progress bars, and many more. There are a number of different frameworks available for displaying data; however, there is no specific focus made on the reason why ReCharts was chosen.

Deployment

It was essential to deploy the dashboard to a web server so that the dashboard could be accessed by the learners, anywhere. The technologies that were utilised in the deployment of the dashboard are introduced in the following paragraph.

Microsoft Azure Microsoft Azure, often only referred to as Azure, is a cloud platform for application management, storage, and networking. It provides a wide range of services, such as virtual machines, storage, API management, and more. For the purposes of this project, Azure was chosen because it is the only cloud provider that allows for the deployment of services to data centres located in Norway, which was an important prerequisite because of the privacy concerns with the data used on the dashboard.

Other Tools

The following tools were utilised during the project, in addition to the tools and technologies described in earlier sections.

Zoom Zoom is a video conferencing platform that enables users to create and manage online virtual meetings. During the course of the project, it was utilised to facilitate communication between myself and a teacher from OsloMet in order to coordinate the development of the dashboard and the exchange of information with the learners. Additionally, it was used to perform testing of the dashboard and conduct interviews with the learners.

Slack Users are able to connect with one another via Slack, a communication platform. It was utilised for communication with my supervisor, for the purpose of scheduling meetings, and for communication with the senior developer at SLATE, who was responsible for access to data from the OsloMet course.

4.2.2 Prototyping

During the course of the desk research, the initial dashboard design concepts were established. Several articles offered nuggets of information and evaluations of the system pertaining to the development of learner-facing dashboards that were supported by research. On pieces of paper and post-it notes, these nuggets of wisdom were written down and then repurposed as prototypes of components and layouts. Following the first round of brainstorming on the dashboard's layout, conversations were held with colleagues and fellow learners regarding the most important aspects of a LAD layout. In addition to the material provided in the literature, the feedback gathered from these "quick-and-dirty" interactions was used to inform the design of the dashboard. Firstly, as Few notes in his paper on "Information Dashboard Design", a dashboard should present only the most important information that is required to achieve one or more goals, and it must be able to fit on a single computer screen so that it can be monitored at a glance (Few, 2013). Additionally, a dashboard should be able to present this information in a format that is easily comprehensible. Second, the research has uncovered three important aspects, the first of which is that people have a restricted capacity for their working memories. Because only three or four pieces of visual information may be held at once, the design of a dashboard ought to make use of well-designed visual displays such as graphs rather than individual bits of text and numbers. Learners will have an easier time remembering what they have observed as a result of this, which also aids their perception. The second and third aspects take into account the significance of characteristics like colour, form, and motion, as well as aspects like closeness, resemblance, and continuity. While the first aspect can be easily achieved by reducing the number of pieces of information that are presented, the second and third aspects require the use of design testing, which can take the form of usability testing, qualitative analysis with the intended users, or any other method that is suitable to refine the design so that the user will have an easy time comprehending the information. The design of the dashboard was not put through testing using any particular method at this point, but the findings of the research in combination with "quick-and-dirty" testing led to the following

design decisions:

- The dashboard should display no more than four distinct pieces of data simultaneously.
- The information presented should be well-designed visual displays such as graphs rather than individual bits of text and numbers.
- The information presented should be surrounded by related information.
- The information presented should use colour, form, and motion to enhance the perception of the information.
- All of the information presented should have a similar appearance, meaning they should all adhere to the same general pattern in terms of colour, form, and motion.



Figure 4.3: High-fidelity prototype of the eduGraph dashboard

Utilising the above-described design decisions, a high fidelity prototype was created in the prototyping tool Figma. Figure 4.3 illustrates this prototype. As can be seen, the prototype limits the amount of information displayed at any given time and relies on graphical representations of information, such as graphs and progress bars, to indicate the learners' progress. In addition, the use of colour for information transmission has been incorporated. For instance, the filled portion of the progress bar is represented by the colour green to indicate that this area is "good," whereas the empty portion is represented by the colour red to indicate "poor." In order to make the dashboard's interface more user-friendly, its style and layout were modelled after those of other popular websites. For instance, the majority of users are accustomed to the logout button being situated in the upper-right corner of the screen, as this design pattern has been implemented by a large number of websites.

Following the development of the high-fidelity prototype, the next step was to implement it using code with React.js. However, to enable the dashboard to function, it needs access to data. It was required to establish a specification detailing how the dashboard would access data stored on the OXALIC servers.

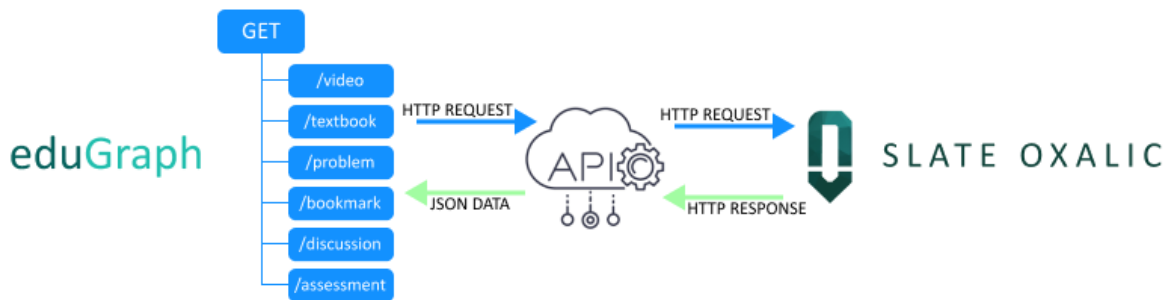


Figure 4.4: API specification model for the eduGraph dashboard

4.2.3 API Specification

Every activity that a user can perform within the Open edX platform results in the creation of a log file, which is then sent to OXALIC for storage. This log file stores unstructured JSON data, which includes information such as the time and date of the event, the user's IP address, the type of event, and the event data. The senior developer at SLATE would create an API that would be used to interface with OXALIC in order to simplify the process of receiving and displaying this data. It was decided that an API specification was required in order to guarantee that the dashboard and the API would communicate in a manner that both pieces of software could understand. In order to construct the API specification, the OAS was used in conjunction with Swagger Editor. A model of the API specification is illustrated in figure 4.4. The API specification includes a detailed explanation of each of the endpoints that it documents by specifying all of the fields of both the request message and the response message. These are broken down into their component parts, with a description for each field, an explanation of the type of data they accept, and a sample response is provided. This makes it possible for the developer at SLATE to easily comprehend the structure of the data that is requested and received, and it also makes it possible for the dashboard to be developed in accordance with the specification, which in turn makes it possible for the dashboard to be built before the API is ready. Figure 4.5 illustrates one of the endpoints that can be reached by the dashboard. The endpoints were created using the information that can be found in the documentation provided by Open edX for all of the events that are conceivable to take place in any given course.

4.2.4 Dashboard Development

Following the establishment of the dashboard's design and the specification of the API that will be used to connect it with OXALIC, the dashboard was developed. The ASP.NET Core

GET
/problem
returns problem interaction events

Parameters

Name	Description
userID <small>string</small>	ID of user to fetch interaction events for
startDate <small>string</small>	Determines from which data events should be returned. If empty, startDate will equal the first registered event date
endDate <small>string</small>	Determines to what date events should be returned. If empty, endDate is equal to today's date

Responses

Code	Description
200 OK	problem_check events matching query (see https://edx.readthedocs.io/projects/devdata/en/stable/internal_data_formats/tracking_logs.html#problem-check-server) Example response: <pre style="background-color: #2e3436; color: #eeeeec; padding: 10px; border: 1px solid #2e3436; border-radius: 5px; margin-top: 10px;"> { "problemId": "string", "attempts": 0, "grade": 0, "maxGrade": 0, "state": {}, "submission": { "correct": true, "responseType": "string", }, "success": "string" } </pre>

Figure 4.5: API endpoint example

framework was used in the development of the back-end, while the JavaScript framework React.js and other frameworks discussed in section 4.2.1 were utilised in the development of the frontend for the dashboard. During the development of the dashboard, it was discovered that authentication and authorisation of users could not be handled by a third-party authentication provider; therefore, the dashboard had to be developed as an Learning Tools Interoperability (LTI) component within the course that the dashboard was being used in. This was due to the fact that users and their credentials were not stored in the OXALIC database but rather on OsloMet servers. Access to the servers was restricted due to privacy concerns. However, an LTI component in the Open edX system has access to the user's ID, which means that the dashboard gains access to the user's ID through the LTI component and then uses the ID to retrieve the user's activity from the OXALIC database.

Figure 4.6 provides an illustration of the two pages of the dashboard. The first page is displayed when the user "logs in" to the dashboard, and it presents the user with a welcome message and some information about the dashboard, the thesis that the dashboard is made for, and some notes about the information displayed. The second page is accessed when the user clicks on the "Progress" button, and is where the information about the learner's activity is displayed.

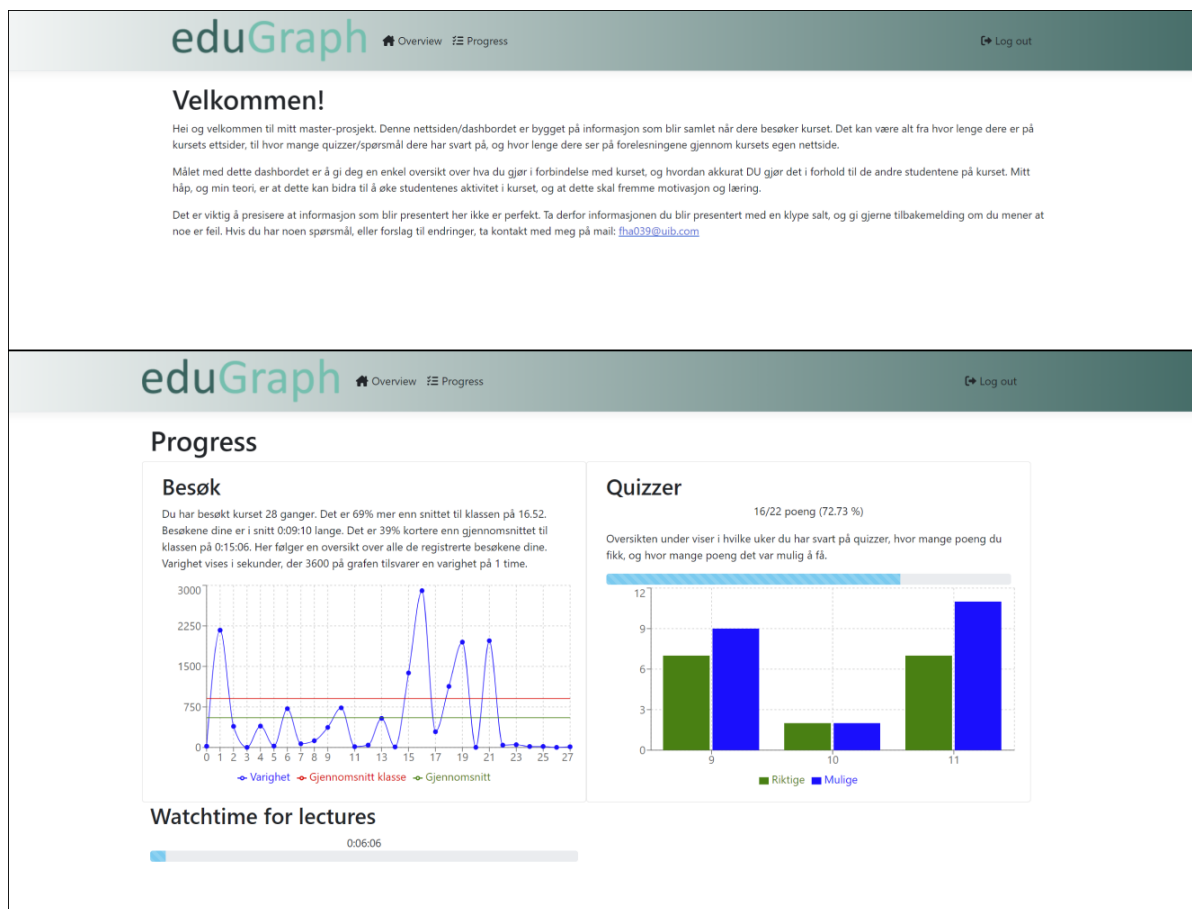


Figure 4.6: eduGraph Dashboard

4.2.5 Testing

A Python framework known as Tutor was required to be utilised so that the deployment of the dashboard could be tested. Tutor is a framework that makes it possible to create local Open edX courses that can then be hosted within a Docker container. The LTI component containing the dashboard was added to the locally created course and then packaged up and hosted in a Docker container. After access to the dashboard was tested, the results concluded that the dashboard was operating correctly.

4.2.6 Deployment

In order to make the dashboard accessible to the learners, it was necessary to incorporate it into the LTI component of the course that was being taught at OsloMet. One of the instructors working on the course had to facilitate the dashboard deployment of the course because of necessary management privileges. After the dashboard was deployed to an App Service on Azure, the instructor received an email containing the configuration parameters for the LTI component. Via Zoom, the instructor then walked through the steps necessary to install the component as advised.

4.2.7 Challenges

Although the development and implementation of the dashboard were very promising and successful in terms of several feedback notes, a number of issues were faced along the way, from the very beginning of planning through the dashboard's actual deployment. Due to miscommunication with the administrator and the instructor at OsloMet, there was little information available on when the course would start, its structure, data permissions, and course length. Following the issues with communication, gaining access to data was problematic due to the data's privacy concerns. The lack of communication with the administrator at OsloMet prevented us from knowing what data we would have access to, which made it more challenging to plan for the project, especially given that we would not have access to the user's credentials. This information was communicated to us after the course had begun, necessitating a reimplementation of user authentication and authorization using the LTI component described earlier.

Several issues pertaining to the LTI component of the course were also encountered. Firstly, the concept of an LTI component was foreign, and research into how the dashboard could be integrated with the course had to be conducted. This required the use of the Python framework Tutor and a Docker container for the creation of a local Open edX course where testing and development could be carried out. Second, there were delays in the enablement of the components in OsloMet's Open edX platform due to enabling LTI components requiring a

restart of the servers, which could not be done on workdays when learners are using the platform. Furthermore, due to management privileges mentioned in section 4.2.6 (Deployment), access to the course was restricted, leaving it hard to confirm the deployment of the dashboard. Nevertheless, the dashboard was successfully deployed, and eduGraph was used and evaluated by selected learners from the course.

4.3 Summary

This chapter has presented the tools and technologies used in the development of the dashboard, along with an overview of the project timeline. Furthermore, the development process has been explained, and challenges faced during development have been addressed.

Chapter 5

Evaluation

This chapter describes the evaluation of the eduGraph dashboard.

5.1 Evaluation Process

Interviews were conducted with three learners who were enrolled in the course and had access to the eduGraph dashboard throughout the course's final two weeks. The interviews were performed as semi-structured interviews. In addition, the learners were asked to submit a score for a number of different features of the dashboard. The interviews were scheduled to take place in a private meeting on Zoom, taking place after the course had been completed but before the final exam. During the interviews, the following questions were posed:

- Did the learners have any comments or feedback about the dashboard?
- What was your experience like using the dashboard?
- How useful do you find the information on the dashboard to be?
- What kinds of information did the learners want to see shown on the dashboard?

In addition to the topics above, the learners were tasked with assigning a point value (on a scale of 1 to 10) to each of the following features of the dashboard, seen in table 5.1.

Table 5.1: Questionnaire

Question	1 (Very poor)	...	10 (Excellent)
How would you rank the usability of the dashboard?		...	
How would you rank the comprehensibility of the information presented?		...	
How valuable did you find the information to be in relation to your motivation?		...	
How valuable did you find the information to be in relation to your performance?		...	
How valuable did you find the averages to be in relation to your motivation?		...	
How valuable did you find the averages to be in relation to your performance?		...	
How likely are you to continue using the dashboard?		...	

5.2 Evaluation Results

The value of the presented information in relation to the learners' motivation and performance was the primary concern of the evaluation. Nevertheless, another objective was to evaluate how user-friendly the dashboard was. Because of this, the findings of the evaluation will be discussed in two parts: the first part will concentrate on the usability of the dashboard, and the second part will examine the perceived value of the content in terms of the learners' level of motivation and performance.

5.2.1 Usability

Regarding the dashboard's usability, the answers were overwhelmingly positive and unanimous. The interview questions that were posed to the learners and the answers that they provided are as follows (translated from Norwegian):

- **What was your first impression of the dashboard?**

Respondent 1: *"I found the dashboard to be clear and user-friendly. I liked the fact that everything was on one page, and that I didn't have to scroll down or click on anything to get all the information."*

Respondent 2: *"I found it to be a bit too much information when I first saw it, and I didn't really know what I was gonna do with all the information. But once I figured out where to click to get to the information about my activity I found the dashboard easy to use."*

Respondent 3: *"Very good first impression, the dashboard appears tidy and there is not too much information which I found to be nice."*

- **What was your experience like using the dashboard?**

Respondent 1: *"It was easy to use, again I liked that everything was on one page so I didn't have to click on anything."*

Respondent 2: *"I struggled to get to the information, I was looking for the traditional 'menu' that I'm used to. I would like to see something done to the text on the first page so I know it is not the information I am looking for."*

Respondent 3: *"It was easy to navigate and I could easily make sense of what I was seeing. But I didn't like that all the text was so close together, I felt like I had to read all the text above each graph everytime, even though I just wanted to see my or the class' average."*

- **How useful do you find the information on the dashboard to be?**

Respondent 1: *"I found it useful to a certain degree. It was nice to see what I have and haven't done."*

Respondent 2: *"It was useful to see that I did around average, it was reassuring that I have done about the same as everyone else, it feels nice to know that I'm not alone in the amount of work I have done."*

Respondent 3: *"It was very valuable to see the information, especially that I was below average. It gave me a sense of urgency to study some more because I didn't want to be worse than the rest of the class."*

- **What kinds of information would you want to see on a dashboard like this?**

Respondent 1: *"I would like to see some more about the different modules in the course. It would also be nice to see deadlines for quizzes and assignments on the dashboard."*

Respondent 2: *"I would like to see information about how much time I have spent watching the lectures, and to see which lectures I have or haven't seen. It would also be nice to see how much time I have spent on each module."*

Respondent 3: *"I think I want to see how long I have watched the lectures and if I have watched all of them. I really liked the quiz score that shows up on the dashboard, so I would like to see how I score compared to the others."*

The learners had no trouble using the dashboard; they thought it was straightforward to navigate, and they felt that the design did an excellent job at effectively communicating the information it presented. In addition, two of the learners particularly noted that they thought

it to be a valuable feature that all of the information could fit on a single page. This further validates the findings from the research conducted by Few that is presented in chapter 2.

According to the comments of one of the learners, "I appreciated that everything was on one page, and that I did not have to scroll down or click on anything in order to acquire all of the information." Two of the learners reported that they found the information that was shown on the "welcome" page to be a bit excessive and that they first did not comprehend what was being presented to them. They would like to see something done to it so that it is more clear that it is information about the dashboard, and after their first visit, they would like to skip this page entirely.

In sum, the dashboard was perceived as easy to use and valuable to the learners, despite the fact that the learners had differing perspectives on the value of the information presented. In addition, they indicated that they would like to see more information in order for the dashboard to have a more significant impact on their learning experience and to be more inclined to use it as a tool in their daily life.

Table 5.2: Evaluation results

Question	R1	R2	R3
How would you rank the usability of the dashboard?	8	6	8
How would you rank the comprehensibility of the information presented?	6	8	8
How valuable did you find the information to be in relation to your motivation?	7	8	8
How valuable did you find the information to be in relation to your performance?	6	9	6
How valuable did you find the averages to be in relation to your motivation?	8	8	8
How valuable did you find the averages to be in relation to your performance?	6	5	7
How likely are you to continue using the dashboard?	7	6	9

5.2.2 Information Value

The goal of this evaluation was to determine how effective the information presented on the dashboard was at increasing the learners' perceived level of motivation and performance. Early results suggest that the dashboard effectively communicated the information it presented and that the learners regarded the information to be valuable. This is evident from the responses provided in the section preceding this one. In addition to the questions previously presented, the learners were tasked with scoring several different aspects of the dashboard on a scale ranging from 1 to 10, with 1 indicating the lowest possible score and 10 representing the highest. The findings of the survey are presented in table 5.2.

As is evident from the results above, the information presented on the dashboard is perceived as valuable by the respondents. They report a high level of increased motivation due to the information they are presented with, both from the information about their own activity and the information they get about how they compare to the average of the class. The value of the information in relation to their performance is, however, not so clear. Furthermore, the respondents are optimistic about the continued use of the dashboard, although not all of them as strongly.

5.3 Summary

In this Chapter, the evaluation of the dashboard has been presented, and the results have been analysed. The results of this evaluation are promising, and the dashboard seems to be a valuable tool for improving learners' motivation; however, due to a lack of respondents, future studies on the topic are recommended.

Chapter 6

Discussion

Here we will discuss the research done, the results, problems faced during research, and answer the questions that were raised.

6.1 Artefact Development

The implementation of the eduGraph dashboard ("Artefact") was carried out in accordance with the "Design Science" research methodology. DS provides a set of methods and guidelines for the design of ISs that proved valuable for the research conducted in this project. The three research cycles of DS, presented in section 3.1.1, were helpful in structuring the research and the design of the dashboard. Each cycle and its respective findings are discussed below:

- The **relevance cycle** is concerned with the discovery of the relevance of the proposed artefact. The environment in which the artefact is developed and the evaluation criteria for the artefact are also established in this cycle. The environment for this research is the Open edX platform, more specifically the VUNG6000 course at OsloMet University, in which the dashboard was evaluated in. After the establishment of the environment, the stakeholders of the research could be identified. Seeing as the Artefact is developed for the course at OsloMet, the stakeholders are the learners taking the course, the course instructor, and the researchers conducting the research. The evaluation criteria are partly based on the research questions presented in chapter 1, and partly on the guidelines for DS Research presented in section 3.1.2.
- The **Rigour Cycle** is concerned with finding the knowledge that applies to the research project. Thorough literature research was carried out to discover the relevant fields of research and is covered in chapter 2. This cycle also established the relevant theories and methods that will be used in the design, development, and evaluation of the Artefact.
- The **Design Cycle** is where the development of the Artefact was carried out. The development of the dashboard was carried out in the context of the research project, guided

by the guidelines presented in section 3.1.2.

Each of the seven guidelines in DS Research has been successfully applied in this research project and will be explained in detail:

- **Design as an Artifact:** The research was successful in producing a working artefact and serves to demonstrate the Artefact's feasibility and potential. In combination with the evaluation of the Artefact, it provides "proof by construction" that the Artefact can solve the research problems presented in this project.
- **Problem Relevance:** The relevance of the Artefact was established in the Relevance Cycle and is demonstrated by the literature research presented in the background chapter.
- **Design Evaluation:** Evaluation is present in the Design Cycle, where prototypes of the Artefact were evaluated with the help of learners and colleagues, and the final evaluation of the Artefact.
- **Research Contributions:** This chapter, and chapter 7, answers the research questions of this project. Furthermore, the documentation of the process of the project serves as the research contribution. This research presents no contributions to theory development. I argue that the evaluation of the Artefact has not been performed with enough learners to make solid conclusions, but that the Artefact seems to be a useful tool for the learners and that it is worth pursuing.
- **Research Rigour:** The research was successful in finding the knowledge and methods that apply to the research project.
- **Design as a Search Process:** The Artefact was successful at discovering an effective solution to the problem presented in this project. Given the results of the evaluation, the Artefact works well enough for the problem it tries to solve.
- **Communication of Research:** This thesis serves as the communication of the research conducted and contains the steps needed to reproduce the results, as well as the results themselves, for anyone interested in details that led to the conclusions of this research.

6.2 Evaluation

The results of the evaluation of the Artefact, which is presented in Chapter 5, indicate that the Artefact can be considered with reasonable success and promising results for future directions. That is, eduGraph demonstrates a usable artefact, and it received mostly positive feedback from the learners who participated in the evaluation. The evaluation is flawed, however, in that there were only three participants in the evaluation, and as a result, the results are not statistically significant. Only three of the five learners who expressed interest in participating in the evaluation of the Artefact, out of the fourteen learners who were enrolled in the course, actually showed up for the evaluation. This can partially be explained by the nature of the course, as it is further education for nurses who are already in full professional employment and partially by the small number of learners who participated in the course. Finding people to take part in the evaluation is a challenging endeavour, as has been demonstrated by a multitude of past studies. In addition, the evaluation only takes into account the learners' own perceptions of the Artefact and the information that is presented to them and does not take into account the influence that the Artefact really has on the learners' learning. Therefore, the evaluation is not a good indicator of the impact that the Artefact has on the process of learning; yet, the preliminary results and feedback from participants are sufficient to support the Artefact's ability to increase learners' motivation and, to a lesser degree, their perceived performance. In order to provide conclusive evidence regarding the Artefact's influence on the learning process, a larger number of learners must be sampled.

6.3 Research Questions

6.3.1 Data Collection

RQ1: What data can be extracted from an edX platform to support learner motivation through a LAD?

As mentioned in the literature review, data about learners' behaviour in learning environments must capture the complexity of the learning process. Therefore, "high-quality" data - data that allows researchers to understand the social and pedagogical components of learner performance - is required. In order to collect "high-quality" data, the collection of data should take place in learning environments in which learners are engaged in authentic learning activities without interfering with the learning process. It can thus be suggested that the Artefact should use Open edX event logs as its data sources. The Open edX event logs contain information about learners' actions in the learning environment, such as their navigation pattern, watch time for lectures, and the number of visits to the course. This suggested data collection method is supported by the literature in that its use is unobtrusive with regard to the learning

process of learners and that it captures the complexity of the process (Khalil, 2018). One of the issues that emerge from these findings is that the Artefact is not integrated with the Open edX platform, and therefore, it lacks the necessary data to make sense of the complexity of the data in regard to the learning process. Furthermore, it can be argued that these findings may be somewhat limited by not being driven by a theoretical perspective in the selection of data. The data that is suggested to be used by the Artefact is the data that is available due to the problems of getting access to the data that is collected by the Open edX platform and data about the course itself. This finding is consistent with that of Verbert et al. (2013), who suggest that making the data captured from learning environments available for research purposes is a complicated process. This can be attributed to the fact that ownership of the data trails generated in digital learning environments has not been resolved either culturally or legally.

However, the results from the evaluation of the Artefact show that the data available to third-party applications on the Open edX platform is enough to enable a successful LAD that can impact learners' motivation and performance.

6.3.2 Design of a Dashboard

RQ2: How can a dashboard be designed to increase learner motivation and performance in MOOCs?

Previous studies evaluating the factors that affect the success of LADs have found that the aesthetic appeal and usability of dashboards directly impact their perceived usefulness and understanding of what it presents (Park and Jo, 2019). Furthermore, Park and Jo found that learners' understanding of the dashboard directly impacted their behavioural changes. It is therefore likely that a dashboard that is perceived as valuable and easy to understand will bring about a more significant change in learners' behaviour and, as a result, have a more significant impact on their motivation and performance. This behavioural change is at the roots of SRL, where learners' self-generated thoughts and feelings influence their behaviour towards achieving a set of goals. It is possible to hypothesise that the increased motivation and performance of learners will enhance their self-satisfaction and motivation to improve their methods of learning, therefore enabling them to better self-regulate. The reason for this can be explained by the fact that learners' motivation to see improvements in their graphs, and more specifically in comparison to the average of the course, leads them to read more of the course material, watch more of the lectures, and to take more assignments, thereby improving their learning which in turn can enhance their self-satisfaction.

Prior studies have noted the importance of human perception considerations in regard to the visual perception of dashboards. Few's (2006) research on Information Dashboard Design has been an important influence to the design of the Artefact, especially his findings of the three notable considerations of visual perception; the number of visual elements, the type of visuals;

and continuity between visual elements. As a result, it was hypothesised that the Artefact should contain a maximum of four visual elements at any one time, all elements should fit on a single screen, and graphs should be used to aid learners' visual perception and memory retention. Furthermore, the visual elements must be similar in style in both their use of colour and their layout. In addition, text accompanying the visual elements is provided to aid learners' understanding of what the visuals represent. As is evident from the evaluation, these design considerations are helpful to convey the information that is presented to the learners effectively and are therefore able to increase their motivation and, to a lesser degree, their performance.

6.3.3 Perceptions of the Artefact

RQ3: How do learners perceive a LAD designed to track their progress and increase motivation?

As mentioned in answer to RQ2, the aesthetic appeal and usability of dashboards directly impact learners' behavioural changes. It is therefore essential to answer the question of how learners perceive the Artefact. Because learners participating in the case study only had access to the Artefact for a limited time, it can be argued that the positive results were due to the Artefact being "new and exciting", in contrast to helpful and effective at impacting learners' motivation. The results of the questionnaire, however, show that learners perceive the Artefact as easy to use, easy to understand, and effective at increasing their motivation. It is important to bear in mind the possible biases in these responses, as mentioned in section 3.4.5. Furthermore, the results of the evaluation show that, although to a differing degree, the learners would want to continue using the Artefact in their learning. These results provide a strong argument that learners perceive a dashboard designed to track their progress and increase their motivation as valuable and effective at increasing their motivation. Further research should be undertaken to investigate the effect of a User-Centred Design approach to the design of the Artefact, and it will likely lead to an improvement in the Artefact's usability.

6.3.4 Personalised Feedback in MOOCs

RQ4: How can Learning Analytics enable personalised feedback in MOOCs?

The fourth question this research tries to answer is how LA can be used to provide personalised feedback to learners in MOOCs. When determining whether LA enables personalised feedback, it is important to consider the fact that some software that is being marketed as LA is nothing more than a rebranding of standard monitoring and statistical tools (Cooper, 2012). While this is a valid concern and perhaps a good description of the Artefact, the information presented has the potential to actually influence learners' learning behaviour, and the Artefact can be described using the definition of LA. The feedback provided to learners is based on the

data that is collected during their interaction with the Open edX course, and it has the power to transform the methods learners use through impact on their learning behaviour. The results of the evaluation show that the information presented to the learners has an impact on their motivation, which in turn can cause behavioural changes. It is, therefore, likely that LA can be used to provide personalised feedback to learners in MOOCs.

6.4 Limitations

Several problems were faced during the project, which caused the focus of the Artefact to be changed multiple times. In addition, problems faced caused the development of the Artefact to be delayed several times, as well as introducing a "scope-creep" into the project. The limitations of this project will be discussed below:

- **Cooperation and Communication:** One of the main issues that were faced during this project was the lack of cooperation and communication between myself and the team at OsloMet. Communication channels with OsloMet were not available until *after* the course had started, and while communication was efficient when questions were raised and problems discussed, there was a lack of understanding of the project and the problems faced. As mentioned in section 4.2.7, the lack of communication with the course administrator at OsloMet caused the enabling of LTI modules for the course to be delayed by two weeks, which in turn caused the evaluation phase of the project to be cut short by two weeks.
- **Privacy Concerns:** Also mentioned in section 4.2.7 were the problems faced due to the private nature of the data. This is a problem which has already been mentioned in the literature. Furthermore, the lack of standardised data formats, and the diversity of data sources, means that sharing of data collected in MOOCs presents a challenge. Paramount is the privacy concern when using data collected from younger learners. I posit that it is imperative to consider using LA tools on younger audiences, as they are more likely to acquire lifelong SRL skills.
- **Data:** As mentioned previously, the lack of standardised formats for the collection of data in MOOCs presents a challenge for sharing and analysis of data. Furthermore, courses are often not able to provide the data needed to enable personalised feedback and SRL in MOOCs. Therefore, future tools must be designed around the course platforms, preferably integrated into the course itself, in order to reap the full benefits of all the data that is accessible. In addition, the lack of possibilities to extend course platforms with external tools is a big problem for the continued research into LA and SRL.
- **Evaluation:** As mentioned earlier in this Chapter, the evaluation of the Artefact suffers from few evaluators. After the initial testing of the Artefact was over, none of the

learners was interested in participating in interviews and answering the questionnaire. In order to overcome this issue, I offered to compensate the evaluators with a coupon for 200 NOK at Foodora for participating in the evaluation. This led to five learners voicing interest in participating in the evaluation, of which three agreed to participate.

6.5 Summary

In this chapter, I reflect on Design Science research, summarise the evaluation and address the research questions that have been discussed and answered. It also presents limitations in the research conducted.

Chapter 7

Conclusion

This chapter concludes the research and provides guidance for the future work of the project.

7.1 Conclusion

The overarching goal of the research presented in this thesis was to develop an artefact that would increase motivation and performance for learners in MOOCs, using the data that was available through the OXALIC system. Even though the research project was not as complete as it initially was set out to be, the results are very promising. Feedback from learners who have used the Artefact was very positive, and the Artefact as a tool enables learners to keep track of their activities and progress in courses and provides personalised feedback to them according to their progress.

One of the most troubling parts of designing a LAD to support feedback and LA is the fact that data is not readily available. Most MOOC platforms are not able to provide the tooling needed to create a highly integrated, effective feedback system. Contrary to the opinion of Siemens presented in his paper on the emergence of LA (Siemens, 2013), I posit that the biggest problems facing LA are, in fact, technical. Even though one of the main issues facing the design and implementation of LADs to support LA and SRL is the lack of accessible data, accessible is the keyword. The data that is needed to enable this is, in fact, there; however, access to it is limited due to technical constraints in the systems that collect data and, more importantly, due to privacy concerns and concerns about ownership of the data. With access to all the data that is being collected in MOOCs, I believe that it is possible for researchers to make better models for SRL and that these models can impact learning on a more meaningful level than has been presented in the literature. Technical expertise is lacking in the fields of LA and SRL, and research into the problems facing them will not suffice. As can be seen from the emergence of agile methodologies for development - the requirements of most ISs today are unknown before the start of a project, and the expectations from users are too high - the time where research into the problem could solve the problem at hand is passed. The ever-changing

environment of today's ISs, and the need to constantly adapt to the needs of the users, will make it impossible to create a LAD from only research. No one knows what the next big IS will be; therefore, technical expertise and knowledge within the field of IS implementation is needed. LA and SRL theories and methods must be combined with the iterative process of developing ISs such as LADs to support LA and SRL in the future. Learners must be able to use the product easily, and they must perceive a value in using it before real impact can be seen on their learning.

To summarise, the artefact produced in this thesis presents a dashboard where usage has seen an increased level of perceived motivation in learners; however, it was not possible to measure increased levels of performance due to a lack of data.

7.2 Future Direction

In order to further improve the effect the presented Artefact has on learners' motivation and performance, some key features should be considered for future work on eduGraph.

Machine Learning/Statistical Analysis The first feature that I would suggest researching further into is the use of machine learning and statistical analysis to present more information about the data. This could allow researchers to understand learners' activity in online courses better and should enable predictions of learners' progress in courses. Furthermore, the use of statistical analysis could be used to identify patterns in learners' behaviour and to identify potential learning problems.

SRL Concepts Several SRL concepts should be considered for improvements to eduGraph. One of the goals of this research was to implement some kind of goal-setting system that enables learners to set goals for themselves and to be able to track their progress towards these goals. This is an important concept in SRL. The backend for this project has already implemented a system that allows for this; however, the frontend would need to be implemented, and the privacy concerns for the storage of this data would need to be considered.

Integrating with MOOCs The dashboard should better integrate with the MOOC courses where it will be used. Currently, the dashboard has access to the course's metadata, but it does not use it in any way. The metadata could be used to display the course's information better and to provide a more personalised experience for learners.

Gamification One of the respondents of the evaluation specifically mentioned how they enjoyed the fact that they could see how they performed compared to others and that it sort of felt like a game to them. This is an important feature that I feel should receive more attention in the future of LA and SRL, as gamification can make learning more fun. Giving learners a

score for each quiz they complete, each lecture they watch, or each visit to the course could be an excellent way to incentivise them to complete more learning-related tasks.

More Visualisations As was mentioned in the evaluation by several respondents, the dashboard would be perceived as more helpful if it included more visualisations and showed more information about their activities. Carrying out a User-Centered Design process in order to improve the design could result in better visualisations that the learners find relevant.

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