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Exploring the Expectations of Learning Analytics: A Study of Student Expectations and Usability Learning Analytics

Figure 1 AI generated illustration of Learning Analytics 10.05.2023 (Canva, 2023)

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Abstract

In the field of Learning Analytics (LA), studies include LA methodology, techniques, tools, and its usability to stakeholders such as students, teachers, and institutions. However, to get a full understanding of how the full system functions, there is a need for more research from the students' perspective as they use and produce the data and are the main stakeholders of LA. The overall aim of this thesis is to investigate and understand students' expectations of LA, with an emphasis on their experiences with online learning environments. In the present instrumental case study, four semi-structured interviews and one focus group interview (n=7) were conducted. Data were interpreted through a social constructive perspective and analyzed by using systematic text condensation, which established different themes used in the discussion. The Unified Theory of Acceptance and Use of Technology (UTAUT) model was applied to interpret the participants' perspectives and acceptance of LA and students' experience with their relationship to different online learning environments. This allows for making assumptions on expectations and understanding how LA could be adapted to interactional and instructional design. Meeting students' expectations is an important determinant in the eventual acceptance of implementing LA services. In the analysis several themes were found, some being "Quality of information", "Use of personal data", "Determined by Numbers", and "LA, help or hindrance to learning?". The study found that students' experiences with online learning environments can help to understand expectations of new technologies such as LA. While most of the students believe that LA can have a positive impact, some also believe it can change their learning and education practices. Furthermore, they had privacy and ethical concerns about data gathering and use. However, those concerns would be less relevant if data were used to improve their learning outcome.

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1. Introduction

Although studies have been conducted to gain insight into how students learn in the online learning environment such as Learning Management Systems (LMS) (Phan et al., 2022), there is limited research in understanding data, insight, and knowledge obtained from such systems using Learning Analytics (LA). Research suggests that it can facilitate learning for stakeholders and affect online learning environments (Ferguson, 2012; Viberg et al., 2022). LA is defined as: "the measurement, collection, analysis, and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs" (Gasevic et al., 2011, p. 5). LA has become a growing field of interest both within research and institutions (Banihashem et al., 2018), and is proving to be an important technological tool for educational institutions that seek to improve the quality of their online learning, such as courses, and enhance students' motivation and decreasing drop-out rates (Ferguson & Clow, 2017; Siemens & Long, 2011). Furthermore, the use of LA can give stakeholders such as teachers, students, researchers, and academic administration a more detailed comprehension of the teaching and learning processes (Czerkawski, 2015).

Online learning environments provide a useful opportunity to gather a vast quantity of data on students' behavior, strategies for collaboration, and engagement levels in learning processes (Leitner et al., 2017). Furthermore, this could help stakeholders to gain insight into different approaches to instruction and learning processes and aid in adapting or improving methods to enhance teaching and learning methods (Siemens & Gasevic, 2012). Collected academic data and activity data on learners can with LA be used to assist teachers and students in decision-making when making choices to achieve wanted learning outcomes. This could lead to more learning and educational experiences. Researchers have recognized the benefits that LA can bring to higher education, yet their adaptation of LA services is still limited worldwide (Tsai et al., 2020; Viberg & Grönlund, 2021).

To successfully implement a functional technological tool such as LA, it is essential to evaluate and explore the expectations of all involved stakeholders, as these can help accurately predict how the system will be used (Davis & Venkatesh, 2004). Davis and Venkatesh (2004) note that it is crucial to examine stakeholders' expectations at the early iterations or phases of development since the stakeholder expectations can at these stages contribute to valuable knowledge in perceived usefulness and acceptance of implementation in new software or features.

In LA the main stakeholders are the students (Viberg et al., 2022; West. et al., 2020; Whitelock-Wainwright et al., 2019). Meaning that it is an essential first step to analyze the expectations of students regarding LA to facilitate the implementation of LA. Meeting stakeholder's expectation will make it more plausible that they accept and adopt the system (Venkatesh et al., 2003). However, students have limited knowledge of LA, yet they have some expectations of what LA should and could provide (Schumacher & Ifenthaler, 2018) and privacy and ethical concerns about LA requirements such as collection, storing, and using students' activity data (Whitelock-Wainwright et al., 2019). Researchers underline that students have not been widely involved in the development of LA technology (Viberg et al., 2022). Factors like these could explain why the widespread implementation of LA has been relatively slow, even in a technologically advanced nation such as Norway (EuropeanComission, 2022). In this research, the goal is to explore first-year pharmacy students' expectations of LA in their education and how they believe learning might be affected.

1.1 Research question

The overall aim of this research is to explore students' understanding and expectations of LA. To achieve this the thesis tries to understand students' expectations through their experience with digital learning environments with an emphasis on participant's current LMS, Canvas. Furthermore, the interest centers around the expectations of LA being an integrated part of their higher education with a focus on privacy and ethical challenges, and additionally, thoughts on how LA services could impact their education and learning. The following study includes participants enrolled in the pharmacy degree program at the Faculty of Medicine, University of Bergen. The study is a small study contributing to a larger research program called FREMFARM. The research questions explore first-year pharmacy student's perspectives on this matter. The following research questions are:

1. What are first-year pharmacy students' expectations of Learning Analytics in Higher Education?

    a. How can the students' experiences with LMS be translated to LA implementation?

    b. What aspects of privacy and ethics do students expect to emerge with LA?

    c. How do the students believe LA will impact their education and learning?

1.2 Background

As humans in the digital age produce an unfathomable amount of information called "big data". The data is created and retrieved from many sources, including sensors for measuring environment data, posts on social networks, photos and videos, and GPS coordinates from phones. In 2018 the International Data Corporation (IDC) found that the 'Global Datasphere' consisted of 18 zettabytes, and predict this to steadily excel to another 175 zettabytes[1] by the end of 2025 (Rydning et al., 2018). During the last decade the use of digital platforms in education has become common, especially the use of LMS (Awad et al., 2019; Letnes et al., 2021). Even in areas of conflict Information and Communications Technology (ICTS) is playing a role to rebuilding education through digital platforms like Facebook, WhatsApp, and YouTube (Alfarah & Paniagua, 2016). Data collected from the users of different systems and platforms can be used in many ways, e.g., to improve the performance of the system on the basis of the data and analysis or share the data with third-party actors (Sørensen & Van den Bulck, 2018, p. 430).

These systems have become an integrated part of educational institutions to administrate and develop degrees, provide online course content for students, and create an online learning environment for students so that they can communicate, collaborate and access learning content from digital devices (Letnes et al., 2021). According to "Statistisk Sentralbyrå" there were around 1,2 million pupils, apprentices, and students enrolled in education in Norway in 2021 (SSB, 2021). These students are interconnected with their institutions through an LMS and produce large amounts of data (Letnes et al., 2021, p. 34). The use and collection of student activity data rapidly growing field of research and practice in the educational sector (Kunnskapsdepartementet, 2022a; Morlandstø et al., 2019), and in the Norwegian sector the general impression from the educational sector seems to be an unclear relationship to the concept and the use of the data causing the conceptualization of LA (Kunnskapsdepartementet, 2022b, p. 11). The collection and use of student activity data actualize dilemmas like pedagogical, ethical, and juridical considerations in collecting, storing and using the data (Kunnskapsdepartementet, 2022b, p. 11; Slade & Prinsloo, 2013)

LA is anticipated to have greater significance in the future of digitalization of education with the further use and development of digital tools and instruments in education(Ferguson, 2012;

[1] To put this in perspective 1 zettabyte equals 1 trillion gigabytes (1,000,000,000,000 GB), further pinning the fact that we live in an age of digital information.

Siemens & Long, 2011). Having this in mind LA main objective is to understand, analyze and report data from an academic setting (Khalil and Belokrys, 2020, s.186).

Before going into the previous research done in LA, it can be advantageous to look at literature that has defined the field. Botnevik (2021) conducted a Complex Network Analysis to find the most influential papers in the research field of LA between 2016 and 2020. This was done by searching for the most cited literature in-between authors within LA research. The final results gave ten highly influential papers from the timespan, and the three most influential papers from 2020 are elaborated here to give a brief background; Ferguson (2012); Gašević et al. (2016); Siemens and Long (2011). Ferguson (2012) provides an overview of the emergence of LA, distinguishing it from other related fields of research. According to Ferguson, LA developed into a distinct field of research around 2010, separating itself from Academic Analytics and Educational Data Mining (EDM). This distinction is seen according to Ferguson (2012) that LA primarily focuses on the 'educational challenges' concerning how online learning improvements can be made. While respectively EDM addresses the remaining challenges technical being finding value from learners' big data, and Academic analytics addresses political and economic concerning the optimization of students' results. Moreover, she notes the occurrence of overlap between these fields since they are part of the educational sectors ecosystem and the question comes down to *"Who benefits?"*(Ferguson, 2012, p. 307), these four combined factors are drivers in LA research. Furthermore, four future challenges are presented: *"1: Build strong connections with the learning sciences[…] 2: Develop methods of working with a wide range of datasets in order to optimize learning environments[…] 3: Focus on the perspectives of learners[…] 4: Develop and apply a clear set of ethical guidelines"* (Ferguson, 2012, pp. 312-313). These challenges are still relevant today. Siemens and Long (2011) paper bears resemblances to the paper of Ferguson (2012), sharing opinions towards challenges that needs to be addressed and drivers factors behind LA. Moreover, they share emphasis on usage and value of big data and what benefits LA can provide for learners and institutions in optimizing learning. In addition (Siemens & Long, 2011) present concrete examples of this in their article. Both papers acknowledge that learners will seek LA features and services from sources outside the LMS in the future. Therefore, also notes that LA have less dependance on LMS data in the future (Ferguson, 2012; Siemens & Long, 2011).

According to Gašević et al. (2016), implementing and using generalizing LA models for student learning outcome should be approached with caution. The authors argue that LA will only be useful if it is specifically designed to accompany the course it is intended for and considers the unique teaching and learning practices of that course. In other words, it is important to keep in mind the context in which the LA will be applied. However, as a researcher, it can be challenging to make comprehensive conclusions from studies since the analysis typically focuses on a limited number of institutions, courses, or specific cases. This makes it difficult to compare studies and draw definitive findings (Gašević et al., 2016). Hence, Gašević et al. (2016) suggested that it is important to conduct more studies that focus on specific disciplines to gain a better understanding of how students behave in LMS and how it impacts them and e need for theory-driven research when using activity data.

Further several authors press the importance that LA should be grounded in theory, further base its interpretations and understanding of data in pedagogy, cognition and learning theory (Ferguson & Clow, 2017; Gašević et al., 2015; Siemens & Long, 2011). Some approaches have been creating generic models for LA to make adaptation of theory easier(Greller & Drachsler, 2012), but other researcher oppose the idea of LA being a “one size fit all” concept (Gašević et al., 2016). In Norway the attention towards the use of LA has increased in the last couple of years. This can be seen in rapports and reviews from official governmental institutions like “Utdanningsdirektoratet”, “NOU” and “Datatilsynet”. In 2015 Senter for IKT i Utdanning (fused with Utdanningsdirektoratet in 2018) translated the SoLAR definition of LA into a Norwegian setting, pressing forward the importance of this field of research in a Norwegian context (Dahl, 2015). Additionally, NOU 2019: 23 “Ny opplæringslov” has an own chapter specifically dedicated to the use of student data in educational setting highlighting and importance of LA, challenges and considerations in implementing LA in a Norwegian. (NOU 23, 2019) Furthermore, (Kunnskapsdepartementet, 2022a) published a rapport written by an interdisciplinary expert panel, concerning LA and addressing four dilemmas arising from LA. These being the need for information and protection of information, learning as individualized and social process, centralization and autonomy and lastly the need for competence and the reality of competence related to LA (Kunnskapsdepartementet, 2022a). This points to the notion that there is interest in the utilization of LA as a research field, both internationally and nationally in Norway.

As stated earlier in the introduction, collecting and utilization of data and LA might have the potential to affect the educational sector in numerous ways. In addition, the main stakeholders affected by this gradual change are the learners. In a report presented by “Direktoratet for høyere utdanning og kompetanse” (Diku) points out that students perceive the academic staff to have sufficient competence in using digital tools in teaching with learning platforms. Yet, the student responses support the notion that there is substantial potential of digitalization in facilitating education (Diku, 2020).

1.3 Previous Research

Higher education institutions are showing increasing interest in LA (Ifenthaler & Schumacher, 2016; Lawrence et al., 2019; Roberts et al., 2016b). Thus, even with the interest, the adoption continues to be low (Viberg & Grönlund, 2021) and despite the efforts of researchers across Europe, Nouri et al. (2019) found that there has been low implementation of learning analytics strategies at the national or European level. Early research in the field show that higher education institutions are examining in using LA to predict student retention (Roberts et al., 2016b). However, recent highlights that LA systems are being introduced in research and some higher education institutions to improve their understanding and support student learning (Silvola et al., 2021). However, big data application for LA to impact learning instruction is not yet widespread and is mostly limited to small projects that aim to comprehend teaching and learning methods (Roberts et al., 2016b). According to Dede et al. (2016) there is a gap between in utilizing student activity data to predict learning outcomes versus enhancing learning and instruction. Furthermore, they suggest that any LA criteria should be in prioritize its effect on improving learning. Additionally, there is a need for further research to understand how students and educators perceive and utilize learning analytics tools and functions (Dede et al., 2016). As LA services strive to create adaptable and personalized learning environments (Bodily et al., 2018; Ifenthaler & Widanapathirana, 2014), they need to be personalized for the student's needs, so that they are useful. Researchers therefore point out that it is important to understand students' expectations of LA features to align them with learning theory and technical possibilities before implementing them (Ferguson, 2012; Marzouk et al., 2016; Siemens & Long, 2011; Viberg et al., 2022).

An essential first step in implementing a functional LA tool is to consider the expectations and attitudes of the main stakeholders of a system; students (West. et al., 2020). As LA aims to improve learning for students and the context it occurs (Siemens & Long, 2011), it is important to analyze what students expectations from LA services, in terms of both their effectiveness and functionality (Viberg et al., 2022), as well as their ethical and privacy expectations (Slade & Prinsloo, 2013; Whitelock-Wainwright et al., 2019). Other terms as students' expectations to design is also important, but less research has been done on these areas (Schumacher & Ifenthaler, 2018; West. et al., 2020). Research show that students are positive to the implementation LA if keeps them informed about their learning and progression (Roberts et al., 2016b; Viberg et al., 2022). However, Viberg et al. (2022) press the importance of emphasizing the differentiation between students, rather than having an heterogenic assumption when it comes to adoption of LA in education. Pointing at different concerns such as new students having need for more attention with self-regulation when learning, the nature of types feedback from LA can differ based on the abilities and needs of students, and students demographic and academic information which tend to differ greatly, can have a significant impact (Viberg et al., 2022, p. 8562). It is important to identify and understand students' expectations of LA to create better student-centered LA services that reflect on their individual characteristics keeping autonomy, facilitating learning and meet privacy preferences and learning needs of students (Selwyn, 2019). Respectively LA can have higher acceptance and success rate when being implemented resulting in enhanced learning and educational outcomes for students, teachers and institutions (Dede et al., 2016; Viberg et al., 2022). Hence, there is a need for qualitative studies on exploring individual differences between students regarding LA.

When implementation of LA institutions can find it challenging to inform students in benefits and risks of LA. Especially considering privacy and ethical issues when it comes to collecting, storing, and using student activity data. Some reasons are that students underinformed and are unlikely to read Terms and Conditions agreements (Khalil et al., 2018; Prinsloo & Slade, 2015). Slade and Prinsloo (2013) notes that there are three ethical issues to consider regarding students' data in LA: "1. The location and interpretation of data 2. Informed consent, privacy, and the deidentification of data 3. The management, classification, and storage of data"(p. 1511). Thus, these issues are not unique to LA and can be relatable to other areas in ethical and privacy concerns when collecting, storing, and using personal data (Presthus & Sørum, 2021; The European Parliament and the Council 2016; Tsai et al., 2020).

However, one concern indicates privacy issues when it comes to data ownership and access to students data (Greller & Drachsler, 2012), especially since data storing and usage may be used without the knowledge or consent of students, putting students in a position where integrity of their privacy is misused (Roberts et al., 2016b). Additionally, Research by Blank et al. (2014) show that students are capable and knowledgeable about making privacy decisions that aligns with their integrity about privacy in the digital system they are using. Meaning that students can make ethical and privacy decisions when it comes to LA. As shown by finding that students had privacy concerns when it comes to LA implementation, with Whitelock-Wainwright et al.

(2019) and other researchers having similar results. Despite this Jones et al. (2020) argues that there is a widespread idea that students are unconcerned about their privacy, further pressing the importance that it is important to examine students expectations of privacy to LA and other related technologies.

Another concern is that students are not actively participating in the development of LA services (Roberts et al., 2017) and are often not given the authority to make decisions regarding the use of their data, despite being a general ethical principle (Slade & Prinsloo, 2013). One result of students being excluded from participating in the decision making could create difficulties of the acceptance of the technology. Ignoring students' and disregarding their involvement, it can create imbalanced power dynamics in higher education environments and present LA as a tool for meeting institutional goals instead of benefiting student learning (Selwyn, 2019; Slade & Prinsloo, 2013). Another consequence of ignoring students' involvement can result in student's low student participation causing less awareness of data gathering and LA. As research indicate that some students are not aware that data different types of data are being gathered on them and lacked understanding of potential usage of the data such as LA practices (Jones et al., 2020; Schumacher & Ifenthaler, 2018). To suit general ethical and privacy guidelines students should be involved both in decision-making and be able to decide what and how personal data should be collected, stored, and used.

Despite privacy concerns, West. et al. (2020) found that some students are willing to trade personal data for learning beneficial reasons. Greller and Drachsler (2012) highlights several benefits for students with LA implementation in education. It can help students gain a better understanding of their learning behaviors through self-evaluation of data, which is crucial for self-awareness. Additionally, LA can offer personalized learning opportunities by allowing students to adjust their learning techniques and providing early intervention services based on their activity and profiles (Greller & Drachsler, 2012). This mapping of student information can be used to direct resources towards achieving their learning goals and improving their knowledge on the given topic (Siemens & Long, 2011).

The most common way for students as end-users, is to use LA is through visualization (Rets et al., 2021), peer comparison (Jivet et al., 2018), feedback (Lawrence et al., 2019), and recommendations (Bodily & Verbert, 2017), they typically interact these services through different learning environment such as LMS. The most common feature that students interact with is Learning Analytics Dashboards(LADs) (Rets et al., 2021), which refers to a personalized user interface or dashboard in a learning environment, that can provide all-encompassing gathering of features such as visualizations that assist students observing and make informed decisions about the learning process, recommendations for learning strategies and tasks(Bodily & Verbert, 2017), reminders and time spent on tasks (Rets et al., 2021).

1.4 Structure of the thesis

The introduction provides the reader with the context of the thesis, background, and previous research, followed by chapter two which offers insight and definitions into the topics used and discussed throughout the thesis. Chapter three offers a theoretical framework that guided the research and gave the results. This is followed by chapter four, which outlines the methodology and data collection used by the researcher. Chapter five presents the analysis and results from the conducted research. The sixth chapter addresses any critical points of discussion found in the analysis, while the seventh and final chapter covers the conclusion and recommendations of the thesis.

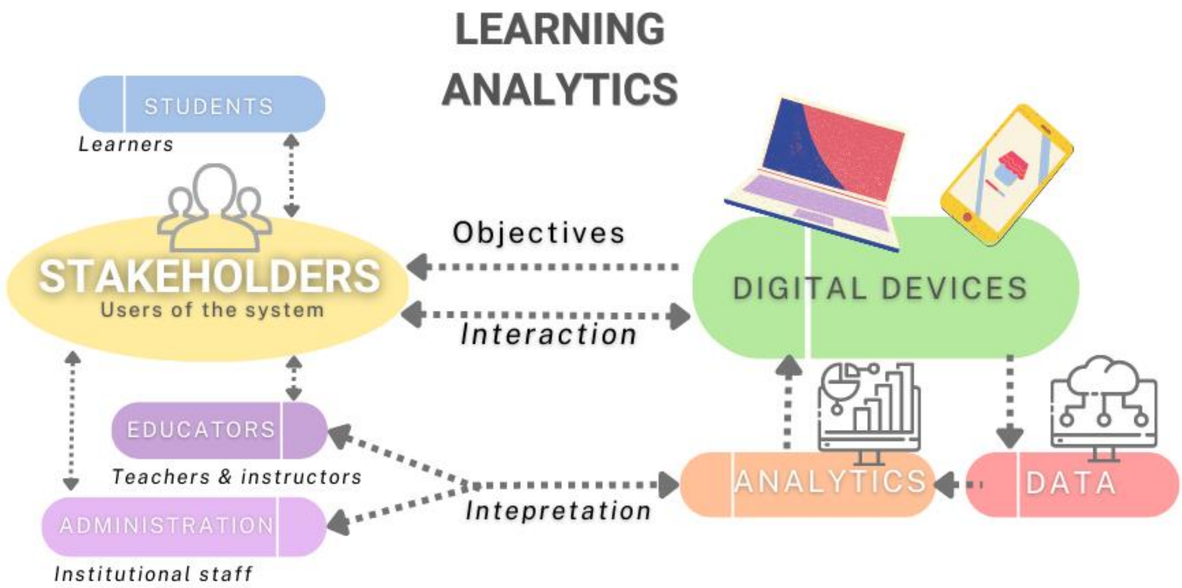
2. Learning Analytics

This chapter will present LA, and present key concepts within the field of research. Further presenting considerations on how LA can be seen in relation to the context of education and learning.

2.1 Learning Analytics

The term LA has been given several definitions over the years, with Siemens (2010) being one of the first to explain it as "the use of intelligent data, learner-produced data, and analysis models to discover information and social connections, and to predict and advise on learning". Putting it differently, LA is the gathering and examination of data that is produced by the learner, which can be utilized to describe or predict academic accomplishment or to give guidance to enhance the learning process. Thus, this explanation of LA does not consider the learning environment. At the 1st International Conference on Learning Analytics and Knowledge (LAK, 2011), LA was defined as: "the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs"(Gasevic et al., 2011, p. 5)

This is later addressed by the researchers Siemens and Long (2011, p. 36) note that “learning analytics centers on the learning process, which includes analyzing the relationship between learner, content, institution, and educator”. Where the authors specify and put emphasis that the environment is a crucial part of LA. However, Wilson and Scalise (2016) points out that interpretation is not precisely included in the SoLAR/LAK definition of LA. The argument stem from that the authors note that although “collection, analysis and reporting”, is defined, the lack of interpretation of results can result in the idea that after the data results are calculated and presented, their meaningfulness for learners and learning is self-evident. The focus of LA is to combine various techniques for transforming data into useful knowledge that can have positive impacts on learners and their environment. Essentially, LA is dedicated to using technology to improve the learning process by relying on interpreting and reporting data analysis, prioritizing the needs of the learners, and hold on to established learning theories.



Figur 2 Illustration of student centered LA made by the author (Canva, 2023)

Figure 2 illustrates an attempt to give the reader a picture of how the process of LA can be interpreted as a technology, and how different components of LA are interconnected. Students interact with digital devices. Their activity data is collected and stored, as data. According to Khalil and Ebner (2015) this collective data is called “Big Data” and consist of interaction data, traces, personal data and academic information. Khalil and Ebner (2015) also points out that these data forms are stored in different ways and consist of different data types. Then these datasets are analyzed using different analytical approaches with influence from “Interpretation” of educators and administrators with preferably emphasis on learning theory, coherence and put into context of the learning environment(Wilson & Scalise, 2016). Then given back to digital devices and provided as the wanted “Objective” of LA outcome, are examined to make decisions, like predicting, intervening, suggesting, customizing the learning, and responding to issues encountered, with examples being descriptive, predictive, diagnostic, and prescriptive LA (Kunnskapsdepartementet, 2022a). “Stakeholders” are those who produce immense amounts of data, those being learners, educators, researchers, and administration. The stakeholders are also the end-users who the analyze is for, with the main stakeholders being the learners (Viberg et al., 2022; Whitelock-Wainwright et al., 2019). The goal is to improve learning outcome and experience and develop the learning environment.

2.2 Sources of Learning Analytics

All types of digital traces, paths, and processes that students leave behind during their learning activities can be saved as data in one form or another. These data types are the foundation of LA. Activity data is a term used as an overlaying term in defining data that is included in LA. The term is defined by Joint Information System Committee (Jisc): “’Activity data' is the record of human actions in the online or physical world that can be captured by computer” (Kay & van Harmelen, 2012, p. NaN). It is also important to note that data recorded in the physical world also can be stored as digital data, such as test scores, attendance, and different achievements. In a Norwegian setting the KS-project ‘Aktivitetsdata for vurdering og tilpasning (AVT) activity data is described: “When a student does assignments, looking at videos or other activites in a digital tool, activity data is generated” *[authors translation]* (Morlandstø et al., 2019, p. 17).

Additionally Wilson and Scalise (2016) adds that the choice of appropriate data types and algorithms is another important aspect to consider when it comes establishing coherent evidence based arguments from LA to support claims about learners and learning outcome. These choices of data types are organized in unstructured, semi-structured and structured. Unstructured learner data usually consists of many different formats, such as video, audio, text, or other multimodal formats. These types of data lack defining rules, tags, and objects so the syntax for analyzing the data by machine readable schemas is more challenging. Semi-structured is not gathered a database, rather the data is normally organized and regulated by protocols or convention guidelines structuring data. In LA these data are usually the sets of activity data or processes which students attend online, and this is generally collected in semi-structured formats that applies for both human- and machine-readable text, object attributes, arcs, and nodes. Examples being Extensible Markup Language (XML[2]), JavaScript Object Notation (JSON[3]) and NoSQL[4] databases (Scalise et al., 2021). Structured data types are primarily gathered from relational databases where data is organized in tables with assigned attributes. Having data with assigned values and keys are can easily added to analytical tools to examine patterns and connections from data. Example being Structured Query Language (SQL[5]) database.

For institutions to effectively use these different types of data it needs to be organized. As LA often uses integration of data from different sources, it has advantages in being more effective when structured (Samuelsen et al., 2021) The value when incorporating different sources of data increases since it can provide a broader picture of students learning (Morlandstø et al., 2019). Additionally, combining data from several sources of a learners' activity data there is possibility to use data progressively with learners' development in courses or create coherence from one topic or course to another (Kunnskapsdepartementet, 2022a). One important criterion for data being effectively combined and exchanged across platforms is the need for a common format when gathering and collecting data. One way of doing this is by standardizing data types that are produced and shared internally and externally. The most common types of formats used in learning technology are *Interoperability* (LTI), *Experience API* (xAPI), *SCORM* og *cmi*5 (Kunnskapsdepartementet, 2022a). In 2016 the "Standard Norges læringskomitè[6] agreed upon using xAPI as a standardized format in LA. This can over time contribute to well-functioning data sharing within LA and provide room for local and smaller institutions to benefit from already existing tool and schemas and tailor them to suit their needs.

2.3 Data Analysis Techniques and Objectives

As noted above we find that LA is a complex process with many steps(Khalil & Ebner, 2015) and focuses on decisions and actions made upon the basis of the analyzed data, and then reporting it back to the learners, or the learning environment. The Society for Learning Analytics Research (SoLAR) presents four dominant objective methodologies: "Descriptive Analysis – insight into the past", "Diagnostic Analysis – why did it happen", "Predictive Analysis – understanding the future", "Prescriptive Analysis – advise on possible outcomes"(SoLAR, 2023)

[2] XML means extensible markup language and describes text in a digital document
[3] JSON, JavaScript Object Notation is JS syntaxes with standard text-based format for representing structured data based.
[4] NoSQL refers to database management that handle large varieties of data models.
[5] SQL programming language in a relational database.
[6] https://www.standard.no/standardisering/komiteer/sn/snk-186/

2.3.1 Descriptive analytics and Diagnostic Analysis

In descriptive analytics can be used to reveal patterns that can help to discover interrelations between data sets, usually through visual displays of figures (SoLAR, 2023). While as Diagnostic Analysis is finding out why things occur. They both utilize the process is exploring data and analyzing the relationships within it is crucial to gaining an understanding of outcomes. This includes the identification and measures of relevant indicators that help in the learning process (SoLAR, 2023). The data used in such analysis can be obtained from a variety of sources, including instructional activities, polls of users, decisions made in the learning process, and the results of standardized tests and assessments. Descriptive analysis are often presented as detailed reports, or through LADs (see 1.3 Previous Research) that often are visual representation of figures or graphs, combining LA features, and vastly used LA intervention (Bodily & Verbert, 2017; Rets et al., 2021). Whereas diagnostic analysis e.g., could try identifying relevant indicators and patterns of behavior among students in certain courses further applying them to other courses. This could help pinpoint where learners need additional support or training. Such analyses are useful at both the institutional and individual levels for evaluating strategies and optimizing learning techniques (Kunnskapsdepartementet, 2022a).

Analytics with descriptive and diagnostic objectives can make use of techniques such as “Time Sequence analysis” that focuses on examining sequence of connections associations between learning behaviors or interactive material to recognize the students' learning. This could then be used by either students themselves who want individualized feedback from their active learning engagement or instructors as a guide to give personalized feedback to their students (Chatti et al., 2012). Another technique is called Visualization technique, this is based on displaying data sets as graphs or illustrations, much like LADs this can enable people to comprehend the information from a range of perspectives and can be beneficial to different stakeholders, as they can analyze the results of their previous learning practices and observe and make changes and adjustments as needed (Chatti et al., 2012).

2.3.2 Predictive analytics and Prescriptive analytics

Predictive analysis is based on combining past records and using statistical modelling. Correlations between various data sets and outcomes such as drop-out rates can give indicators for trends and estimations (SoLAR, 2023). Similarly, Prescriptive analysis gives assistance on potential results were the aim is to provide advice and recommendations on measures, decisions, and actions that should be taken (SoLAR, 2023). It attempts to anticipate and identify what kind of support may be needed for students. It does this by analyzing both the background information of students and the data gathered from their learning activities. The end goal of predictive analysis is to provide an understanding of the possibilities for different outcomes. Whereas end goal of prescriptive analysis is to enhance learning for students and assist institutions improving courses and study programs (Kunnskapsdepartementet, 2022a).

Institutions can utilize the results from this to evaluate the quality of education they provide, thus allowing them to make changes and intervene if needed. Teacher and students can identify or foresee the problems they or may be facing in teaching or studying, take action to eliminate them and provide any assistance or act upon the results if needed (Gašević et al., 2015; Leitner et al., 2017). A typical technique used in predictive and prescriptive analysis is the decision tree. Decision tree is a classification model that represents the connections between data items in the form of a tree-like structure. It is utilized to make predictions for new scenarios, based on the models from analyzing existing cases (Kausar et al., 2020). In other words, data is funneled with the starting point at the stem of the tree, and as it makes decisions it forms branches. This method is intuitive, and analysis can be observed and tracked which brings us to the next section. However, more complex analysis can use statistical modeling and machine learning, which can give actionable recommendations for both learners and other stakeholders (Kunnskapsdepartementet, 2022a).

All of these LA objectives has importance in the field of research, and can play a greater part in the years to come in relation to further development of artificial intelligence (Chatti et al., 2012; Kunnskapsdepartementet, 2022a; Leitner et al., 2017).

3. Theoretical framework

In this chapter it is presented why there is a need for theory when approaching implementation and use of new systems or features in organizations and institutions. Furthermore, there will be a brief exploration of critique and some central theories that have contributed and led to the Unified Theory of Acceptance and Use of Technology (UTAUT) used in this thesis. The purpose is to give the reader a substantial backbone with critical lenses when evaluating chapter 5. Analysis and .

3.1 Establishing the assemblance of theoretical framework.

The field of education has undergone significant changes due to the progress made in information communication technology (ICT). Nevertheless, the implementation of ICT does not necessarily ensure a successful outcome and can often result in insignificant results in achieving envisioned goals (Davis, 1989; Venkatesh et al., 2003). As noted earlier one of the most widespread ICT implementations in educational sector is LMS (Awad et al., 2019; Letnes et al., 2021), a system that have many promises in providing numerous of features for students and teachers. Yet, studies show that students limits their use of LMS only to a limited amount of those features (Back et al., 2016). This points to a technology utilization-acceptance gap that can pose a significant challenge for institutions when adopting and implementing technology, considering the potential implications. It is crucial to address this gap to ensure successful technology utilization. This means meeting stakeholder expectations is an important determinant in the final acceptance of an implemented service such as LA (Brown et al., 2014).

Around thirty years ago, the research community began showing an increased interest in the acceptance of technology within both private and organizational settings (Davis, 1989). Back then there were limited options for accurately measuring user acceptance of computers and systems. Many of the subjective measures used were not validated and their correlation to actual system usage was uncertain. Davis (1989) presented the Technology Acceptance Model (TAM), TAM is a highly influential theory (Venkatesh & Davis, 2000) that aims to model users actual end-point system use, and how they accept and use technology. The model has roots in several disciplines and theories. Davis (1989) based TAM upon research, he suggested two new variables: "Perceived Usefulness" (PU) and "Perceived Ease of Use" (PEU), which were believed to be crucial factors in determining user acceptance. PU is defined as: "the degree to which a person believes that using a particular system would enhance his or her job performance" (Davis, 1989, p. 320) and PEU defined as "the degree to which a person believes that using a particular system would be free of effort" (Davis, 1989, p. 320). These variables were validated for their effectiveness in predicting user acceptance. The theory is based upon several prior theoretical such as theory of reasoned action, theory of planned behavior and self-efficacy theory (see more: Davis, 1989, pp. 320-323; Venkatesh & Davis, 2000; Venkatesh et al., 2003).

These theories offer general understanding about the fundamental attitudes of individuals, making them relevant to various research fields beyond information system management. Furthermore, these models presented various viewpoints based on the variables incorporated in each of these models, including subjective norms, motivators, attitudes towards technology, social factors, experience, and facilitating conditions. (Venkatesh et al., 2003). TAM has undergone consistent examination and development, with TAM2 (Venkatesh & Davis, 2000) and The Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003) being the two significant further developments.

Despite the wide influence and use of TAM, the theory is criticized by the research community. According to Chuttur (2009) there is skepticism by some in the research community when it comes to application and theoretical accuracy, being limited in explanatory, predictive and practical value. These claims are also supported by Bagozzi (2007) which further notes that the model is a deterministic model, meaning that Initially, it was believed that an person's actions were entirely based on their intentions. However, Bagozzi (2007, p. 246) point out that people can evaluate and reflect on their intentions. This process can lead them to modify their intentions or choose a different course of action altogether. Therefore, intentions are not always fixed and can be subject to change. Further adding that TAM limitations are crucial to address , since it is regarded as simplistic and disregards significant factors and procedures, and the latest patchworks such as TAM2 and UTAUT appear to be a collection of fragmented and unorganized modifications (Bagozzi, 2007, p. 252). Pointing out that "UTAUT is a well-meaning and thoughtful presentation. But in the end we are left with a model with 41 independent variables for predicting intentions and at least eight independent variables for predicting behavior" (Bagozzi, 2007, p. 245). The critique pointed out by the author is important to consider when approaching the theoretical framework of UTAUT.

3.2 Unified Theory of Acceptance and Use of Technology

UTAUT is a theoretical framework developed by Venkatesh et al. in 2003 to explain user acceptance and use of technology. The researchers developed the model with a goal to provide a unified and holistic understanding acceptance of technology. To achieve this goal, various theoretical models related to technology acceptance were examined from distinct fields of research, including social and behavioral psychology and information system management. The aim was to identify both similarities and differences among these theories in terms of their theoretical and contextual frameworks (Venkatesh et al., 2003). Given the source of unifying several models and extracting those seen as most useful has advantages. On the one hand that the existing theories are supported in the research community, on the other they have structured ways of analyzing and reaching results. the UTAUT model proposes that the utilization of technology is based on behavioral intention, with the probability of adopting the technology being influenced by four key factors: Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions. (Venkatesh et al., 2003). See figure 3 for an illustrated overview of the UTAUT model with key concepts and influencing elements that impact behavioral intention and use behavior.

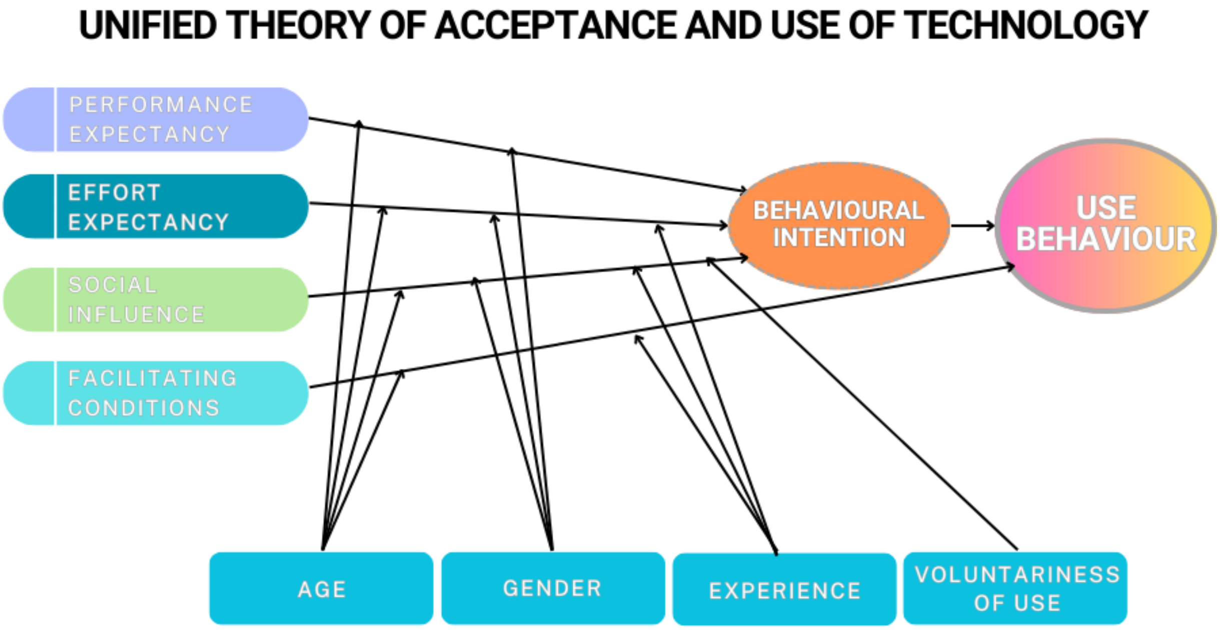


Figure 3 the UTAUT model from(Venkatesh et al., 2003) illustrated by author

Performance Expectancy refers to the extent to which a user has faith that utilizing a technology will enhance their performance or simplify completion of their tasks. The key factor of performance expectancy is established on the ideas and principles derived from TAM, TAM2, combination of TAM and TPB, Motivational Model, model of PC perceived usefulness (MPCU), Innovation Diffusion Theory (IDT) and Social Cognitive Theory (SCT). From these theories root constructs such as Perceived Usefulness, Extrinsic Motivation, job-fit, Relative Advantage and Outcome Expectations are the most central root concepts that support the concept (see Venkatesh et al., 2003, pp. 447-449). To comprehend how students will respond to the features provided by LA, it is crucial to consider their expectations regarding performance. If students perceive that LA can aid their learning progress or facilitate task accomplishment, they may choose to use these services. Therefore, performance is a key factor in determining students' attitude towards the benefits of LA.

Effort Expectancy is the second key concept that refers to the user's perception of how effortless and easy it will be to use a particular technology. This factor is formed on the ideas and principles gathered from theories such as TAM, IDT, MPCU where perceived ease is a central construct of these theories and share similar definitions and scales of the term.

Furthermore, effort expectancy alters its effort impact after prolonged use of technology, declining into being less significant gradually (Venkatesh et al., 2003, pp. 450-451). When utilizing LA to facilitate learning, it is crucial to consider the extent to which a student perceives the use of certain features to be effortless. The ease or difficulty of using these features can significantly impact a student's behavior, regardless of whether the task is compulsory or optional. Students are likely to avoid LA features that are complex or perplexing, while they are more likely to leverage those that are user-friendly.

Social Influence, the third key concept describes the amount of pressure that an individual feels from their peers to utilize a particular technology. Comparable, and image constructs, and in combination with TPB, MPCU and IDT in the way that that individuals modify their actions based on how they believe others perceive them. When technology use is required, social influence plays a critical role, as individuals may use technology not because they prefer it, but because they are obliged to do so to comply with regulations. This implies that in mandatory situations, personal preferences may not be the primary factor influencing technology use.(Venkatesh & Davis, 2000; Venkatesh et al., 2003, pp. 451-453). Social influence is an interesting concept that might have influence on usage of LA features for students. On one hand, the student might become more ‘aware’ of the fact that the learning is being observed, hence behavior is altered accordingly. On the other hand, taking advantage of such features might provide a social acknowledgement in specific facilitated group cultures having an impact on a student’s perception of themselves or others perceive them. Adding these up students and teachers have social influence to alter others behavior and attitudes towards services and features provided by LA.

Facilitating Conditions is the fourth and last concept and refers to how much a user perceives that their environment encourages the utilization of a particular technology (Venkatesh et al., 2003). And has similar perspectives as TPB and combined with TAM, MPCU and IDT when referring to compatibility, perceived behavioral control and facilitating condition constructs. (see Venkatesh et al., 2003, pp. 453-454). According to the model, the act of using something has a direct impact on the intention to use it, but this effect diminishes over time. As a result, the model suggests that the presence of facilitating conditions has a direct and meaningful impact on the user behavior. When referring to Facilitating conditions in students’ expectations to facilitating conditions we can understand it as to what degree which the students believe that institutions and technical infrastructure are facilitated to support these LA features. This can be reflected in how institutions take advantage of student’s activity data, and are implementing them in constructive ways, preserving privacy, learning design, and are given enough resources to use and take advantage of services and features provided by LA. In addition, the sense that institutions have control over what is being provided by LA and supporting with guidance in the use of this technology.

Furthermore, in Figure 3 we see an illustration of the UTAUT model. Here we see that Venkatesh et al. (2003) adds the moderation effects of age, gender, experience and voluntariness of use to the model that can influence to what degree predictors have an impact. In other words, it gives the key predictors' aim to determine how influential the predictors are on the intentions. The impact of the four predictors is influenced by age, while gender affects the connections between effort expectancy, performance expectancy, and social influence. Experience determines the intensity of the links between effort expectancy, social influence, and facilitating conditions. The moderating effect of voluntariness of use is limited to the relationship between social influence and behavioral intention (see figure 2). It offers a unique perspective by comparing different theories that focus on technology acceptance, which often have conflicting or incomplete viewpoints. Through its analysis, UTAUT has found that the factors it proposes explain 70% of the variation in the intention to use technology according to Venkatesh et al. (2003, p. 439).

Venkatesh et al. (2012) developed another extension to the UTAUT model in 2012, that could help explain the use of technology by costumers, in comparison UTAUT had more focus on employees. UTAUT2 adds another factor called "Price value" referring to the decision a consumer makes to weigh the advantages they perceive from using an application against the financial cost of using it (Venkatesh et al., 2012, p. 161). One can argue if students are either employees or customers of a digital learning environment. On the one hand when students pay tuition fees to attend a university, they become customers who receive education and other services in return. On the other hand, they are also required to take on certain obligations, which resemble those of employees, including attending classes, submitting assignments, and passing exams. Thus, students work towards their personal academic progress as well as the institution's overall success.

In the context of this thesis, Norwegian students pay just a small amount of tuition fee, and therefore one can argue that they tend to lean more towards traits of an employee of an institution that benefits from having students enrolled. Comparing these two models against each other, the UTAUT model is more suitable for exploring students' expectations and acceptance of LA technology in their degree or educational program. All though, the theoretical framework is criticized for combining too many theories and still not able to be whole encompassing when it comes to understand use and acceptance of users in a digital environment (Bagozzi, 2007). However, UTAUT key concepts and moderating effects helps establish clear boundaries and limitations of the analysis and scope in the thesis.

4. Methodology and research design

The intention of this chapter is to address and ensure that qualitative research methodological values and principles are maintained in this thesis. The first part of this chapter presents and justifies a social constructivist as the scientific position of this paper. The second explains considerations taken when choosing research design. The third presents the research process from start to finish. The fourth part presents the systematic text-condensation approach of analyzing data. The last three parts will elaborate on how validity and reliability is ensured, the ethical reflections taken into consideration while conducting this study and lastly point out that no research is without limitations.

4.1 Social-constructivist approach to students' expectations

Methodology is within scientific research the *path to the goal* (Kvale & Brinkmann, 2009, p. 199). One way of starting the path would be in taking a stance on how knowledge is understood in the thesis. Identifying this helps the reader understand what lenses to equip. Additionally, it is essential for justifying how the research interprets and values empirical data. When conducting qualitative research, the researcher can take different positions within the philosophy of science. This consideration stems from how knowledge is perceived and conceptualized (Postholm et al., 2018, p. 46). In other words, this implies that the researchers' position will have an impact on the research and how information is pursued and what information is identified as meaningful. The researchers scientific position can also facilitate a framework during the research (Thagaard, 2009, p. 35). This perspective will influence how to interpret and understand statements received from the first-year pharmacy students participating in this research.

This thesis draws inspiration from the social-constructivist perspective. When applying this approach in the thesis the goal is to define informants' statements when they describe features in a social context. In the context of this thesis, it would be how they elaborate and describe their experience and expectations with LA within the context of their education. When conducting qualitative research interviews there is a dialog between humans where they exchange knowledge, perception and understanding. This perspective became evident during the interviews when the interviewer's knowledge and experiences can support or expand the informants' statements though follow-up questions.

According to the social-constructivism viewpoint the empirical data is understood as knowledge that is collectively created and established between the researcher and the participants. The perspective points out that the relation between researcher and informant can impact how the informants describe their experiences, and that both influence the process of knowledge (Postholm et al., 2018, p. 49 & 118). During this research it is therefore reasonable to assume that the researcher and participants were equally involved in constructing knowledge in the dialog and influencing empirical data. This was especially noticeable when investigating what informants were referring to when they used technical terms such as "data" and "privacy". In such cases it was important to attempt to align knowledge constructs of those terms between the informant and interviewer. In doing so, the process of understanding the participants answers and reflections can be more valid. On the one hand the approach assists the researcher in having supportive guidelines when interpreting what the informants are articulating and expressing in their statements. And on the other hand, it can make it easier for the reader to understand assumptions and conclusions made from the participants' statements.

4.2 Research design

As pointed out in 1.1 Research question, this study aims to explore students' expectations of LA. The research question bears the resemblance of the exploring kind, with the intention of looking into how students understand their expectations and acceptance LA and how they believe it can influence their learning and education. Researching these topics require questions that delve and dive into the deep, which resembles a common theoretical approach Postholm et al. (2018, p. 62), giving nuanced data and giving room for different interpretations of LA, and also takes the context into account. Qualitative methodology is consequently an adequate choice in this thesis because it is defined by its openness and flexibility (Postholm et al., 2018, p. 113). The articulation of the research question is essential for choosing research design, since reliance on the right formulation will justify methodology and is used to facilitate and specify the objectives of the thesis (Postholm et al., 2018, p. 58). These points mentioned above are taken into consideration when constructing the research question and design, providing transparency, and giving detailed description of crucial steps taken when conducting research process. Furthermore, the author of this thesis has conducted and been involved in every step of the research process.

When conducting research, it is important to consider the research's specific focus, the individuals or groups being studied, and the methods that will be used to carry out the research. (Thagaard, 2009, p. 48). As stated above the social-constructivist epistemology establishes its foundation on a person's perspective of reality, with reality in constant fluctuation and subjective interpretations. With this approach the social reality is constructed and reconstructed over time (Postholm et al., 2018, p. 61). Hence, in this study the participants' statements are examined in relation to, for example, the context of the conducted interview. Furthermore, opening the possibility of participants constructing new subjective knowledge after interviews. This can be the case when questioning students about LA, since the concept is new to them and their understanding of might be limited. Thus, their firsthand expectations of LA are valuable insights.

4.2.1 Qualitative methodology and justification

To explore the perspectives of a relatively small population of students' expectations to LA, qualitative research approach is suitable. In comparison quantitative research is suitable for when we want to gather information with limited set with selected factors in a big sample, while qualitative methodology is better suited when the goal is to gather more elaborated and deeper information from a smaller data sample (Postholm & Jacobsen, 2018, p. 110). The target group in this study is first-year students in pharmacy degree at UIB. Combined there are 31 students enrolled in this degree making up a small population in research. During the research it is emphasized that objective is to comprehend the significance behind individuals' behaviors, perspectives, and beliefs when it comes to statements that the first-year pharmacy students. Meaning that this study seeks to investigate and interpret students' perspectives that are related to the research question, rather than measuring them.

Furthermore, this will have a benefit of comprehending the complexity of students' expectations towards LA. Hence, a goal is to discover and understand statements that provide detailed and comprehensive insights into people's emotions, experiences, and perspectives related to their experience with LMS and expectations towards LA in their education. Moreover, qualitative research allows for flexibility and adaptability in research design, giving researchers the opportunity to modify their approach as they learn more about the subject matter (Postholm & Jacobsen, 2018, p. 90). The detailed insight and adaptability of the qualitative approach is key when exploring students' expectations to LA. As research has shown that students might have varied or limited knowledge and awareness when it comes to this topic, therefore having the ability to adapt for example the interview guide in a semi-structured to meet each individual during the research is supporting the choice of this methodological approach.

4.2.2 Instrumental case study

The research approach bears resemblance to an instrumental case study design. Instrumental case study differs from other case study approaches in the way that the case itself is a secondary part of understanding a particular phenomenon. In other words using a specific case as a means to gain insight into a larger phenomenon (Mills et al., 2010, p. 474). In this context the case is a specific group of first year pharmacy students from UIB and “to provide insight into a particular issue, redraw generalizations, or build theory” (Mills et al., 2010, p. 474). Therefore, the primary part of the study is students’ expectations of LA in their education. In addition, be able gain a deeper understanding of the factors that contribute to expectations they have towards it. By focusing on a single case like in this research, readers and researchers can develop detailed knowledge that can inform broader theories and hypotheses in future research on LA in similar contexts (Mills et al., 2010). To capture the complexities of the phenomenon and to provide rounded, detailed information to answer the research question, the instrumental approach is suited for finding expectations from students to a specific topic they might have limited understanding of. Thus, this does not enable instrumental case studies generalization in a statistical sense, but rather try to identify themes and patterns that can be compared to other cases. Meaning that an in-depth exploration of a particular phenomenon case can be compared with other cases, in order to make the reader see the transfer-ability of the case findings (Mills et al., 2010, p. 375). Underlining that findings form this study have value for the FREMFARM project in improving pharmacy education.

4.3 Data Collection

This sub-chapter presents how the data collection was conducted. The data was collected with emphasis in gathering data that can describe answer the research questions in a specific context. The context for the students is learning and achievements in their educational degree, and the LMS as their main digital learning environment. The first part will describe how and why participants in the study were chosen and elaborate how the interview guide was designed. Furthermore, what type of interview style was used and how the empirical data was transcribed.

4.3.1 Participants sampling

The sample in the study concerns the part where the information in the research comes from. Within qualitative research it is normal to conduct strategical sampling, which implies that the sampling consists of choosing participants that have qualifications and attributes relevant to the research question (Postholm et al., 2018; Thagaard, 2009). As described earlier, the study is concerned with students enrolled in the pharmacy program offered by mitt UIB, the study chose first year students enrolled in pharmacy. Criteria for selecting the subjects were as follows: first year students on the pharmacy education at UIB, accepted participation in FREMFARM, and users of Mitt UIB. Participants were accepted when they agreed to participate in the interviews and matched the description above. This defines who the participants should be, hence, it is classified as purposive sampling (Etikan et al., 2016). This method involves selecting participants that meet the specific criteria mentioned as the target group above. Which implies an advantage in gathering rich empirical data about first year students in pharmacy at UIB and their expectations to LA in their education. Thus, disadvantageous that it can be biased because of narrow selection criteria.

4.3.2 Interviews

The intention for organizing and conducting interviews on the target group is to gain a deeper understanding of first year pharmacy students understanding of LA and how it can play a role during their studies to facilitate their learning and learning outcome during their time as students. The study includes 7 participants (n=7), with 4 face-to-face interviews and 1 focus group interview with 4 participants. One participant from the focus group interview was asked to take part in a face-to-face interview. The interviews each lasted a bit more than 1 hour.

According to Kvale and Brinkmann (2009, p. 46) an interview in a research context can resemble an everyday conversation, but with research purposes. This can be compared with Cohen et al. (2007, p. 350) definition being an interview being ordinary meeting, where the interview not only being an information consultation, but also a social gathering where interviewer and the informant are co-creating meaning between each other. In other words, this means that the knowledge is altered and created between the interviewer and informants by exchanging concepts and ideas related to the topic during the conversation. Interviews in qualitative research are often divided into three categories; structured characterized by a strict interview guide and inflexible, unstructured, none or vague interview guide participants are speaking freely but guided by a prepared interviewer about the research topic. In the middle ground of these two types we find semi-structured interviews (Postholm et al., 2018, pp. 120-121). A semi-structured approach was used in this research. This gave all the interviews a similar progressive buildup, not too rigged, but rather flexible following the interview guide.

The interview guide was designed to explore and understand the constructs that participants have from topics related to the research question. To gain insight into participants' understanding and expectation of LA, the interview guide began with broad open-ended questions in how they perceive technology usage on a regular basis (See APPENDIX 1). E.g., thoughts about the of activity data gathered from general online activity and perception about ethics and privacy. After answering the broad and general questions they were asked how it could fit in an educational setting, and further into their online learning environment on CANVAS Mitt UIB. The reason for this approach was based on two prior pilot interviews done in advance of this research. During the pilot interviews findings where that the participants had challenges grasping the complexity of LA as a concept and struggled to convey their expectations into a specific context. These interviews were valuable to modify the interview guide and prepare for the interviews in this study.

As a result, the guide had emphasis on developing an interview guide that avoided asking technical or advanced questions to prevent stagnation during the interview. Rather having more advanced follow-up questions that fit the current knowledge constructed between interviewer and participant. Additionally, questions were left open-ended throughout the interview guide. Hence, with the intent of letting the participants have room to unfold on those topics they wanted to elaborate more on. This resulted in an unproportional distribution of empirical data between participants. For example, some participants had more to say about privacy and ethics and others had less.

4.3.3 Transcription

As part of the analytical process the audio recorded interviews were listened through and transcribed. To transcribe, means to transform, in other words shifting from one form to another (Kvale & Brinkmann, 2009). Most of the interviews were auto transcribed with the help of "Word 365 Online"[7], followed by editing and correcting while listening to the interview simultaneously. As this approach did cause major sorting and spelling errors with the focus group interview the software "Nvivo 12[8]" was utilized to transcribe the audio file.

When transcribing interviews there is always a challenge to perceive all the information that occurs and takes place in a physical conversation face-to-face. The researcher must recognize that some parts of the data will be lost during this process. These data include body language, pitch of the voice, annotations and sequences of breath are difficult to render and reproduce. Further the occurrence of irony or oral expressions can feel redundant and out of context when

[7] The transcribe function changes spoken words into written text, and separates the dialogue of each speaker.

[8] Qualitative Data Analysis Software used to analyze documents, transcriptions, and surveys. Tool for insights and understanding of data.

transcribed directly. In other words the data needs to be handled with care and presumptions that these challenges exist and are present during the analysis, and make room for decontextualization of the interview conversation (Kvale & Brinkmann, 2009). The transcription style in this research the words and vocal expressions stated are written literally word-for-word. The transcription mostly excludes the dimension of emotional expressions, short breaks, and annotation emphasis, but with some exceptions where it might be relevant to include strengthening statements or avoid misunderstandings. Since the transcriptions are not being used for detailed analysis of language, but an analysis was focus on descriptions, phenomenon, experiences, and expectations the inclusion of those dimensions above would be redundant and unnecessary extra amount of work. In other words, the transcriptions were precise to speech, and valued some emotional expressions where it seemed relevant to clarify statements from the participants.

4.5 Data analysis with Systematic Text-Condensation

When analyzing data with systematic text-condensation, we take a position of looking descriptive and explorative when handling data material. Based on phenomenological ideas this method makes use of thematic cross-case analyses of various types of data and has a pragmatic approach with four steps.

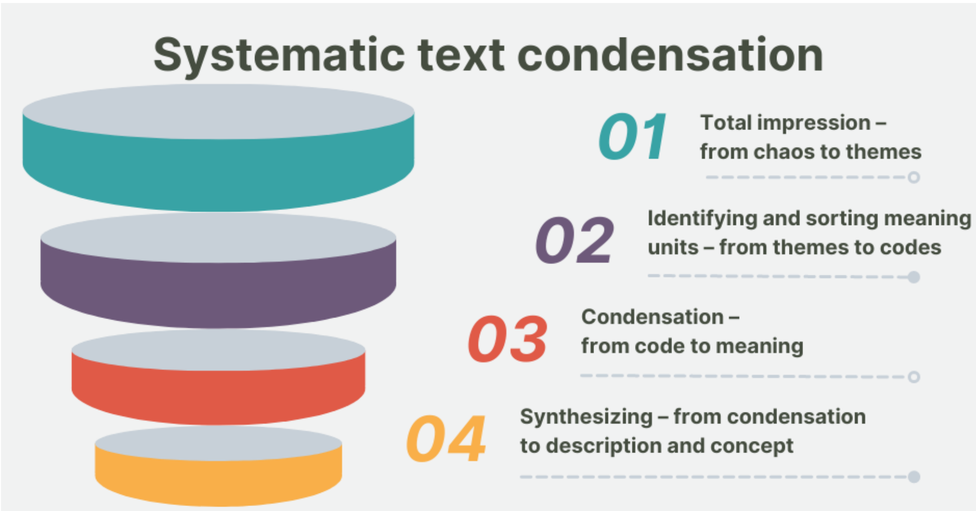


Figure 4 Systematic Text-Condensation by (Malterud, 2012) illustrated by author

In Figure 4 a hierarchical structure is illustrated based on the systematic text condensation by Malterud (2012). According to Malterud (2012) these are (1) ‘total impression – from chaos to themes’ (2) ‘identifying and sorting meaning units – from themes to codes’ (3) ‘condensation – from code to meaning’ (4) Synthesizing – from condensation to description and concept (Malterud, 2012, pp. 795-805). Advantages with this analytical method is that various theoretical frameworks can be applied and offers the researcher a strategy for *“intersubjectivity,* *reflexivity, and feasibility while maintaining a responsible level of methodological quality"* (Malterud, 2012, p. 802). In this thesis some main code themes were highlighted by the condensation: "Quality of information", "Experience with LMS", "Use of personal data", "Data Awareness" "Determined by Numbers", "LA, help or hindrance to learning?" and "Usage of LA". This approach improved meaning making from empirical data and facilitated a strategy for a structured strategy for the analysis in this thesis.

4.6 Validity and reliability

This chapter is dedicated to accounting for choices made to secure the quality of the study. The intention of open considerations of methodological choices is to give the reader the opportunity to evaluate the quality of the research (Thagaard, 2009). According to Cohen et al. (2007) there are different forms of validity, the two most important being internal and external validity. Internal validity according Cohen et al. (2007, p. 135) addresses to what degree the results from the study is applicable to the sample group and the phenomenon that is examined. To ensure internal validity in this thesis has established a clear and detailed research design. By describing the research context, participants, and methodology the findings can ensure some degree of transferability. Furthermore, the research has used credible analytical framework and taken advantage of Kvale and Brinkmann (2009, p. 118) seven suggestions in an interview study. Through this the research aims to ensure internal validity.

External validity addresses to what extent the results from the research could be generalized to other similar cases (Cohen et al., 2007, p. 136). Although the study's sample size is relatively small, it is important to note that qualitative research can be difficult to generalize (Postholm et al., 2018, p. 238). Lincoln and Guba (1985, p. 219) argues that a more fitting term therefore is 'transferability', referring to how well this study could be transferred to another context gaining similar results. Hence, the finding could be different when applied to students from other disciplines, further elaborated in later (4.8 Limitations). However, the insights gathered from participants can provide valuable information and contribute to a broader understanding in how first-year pharmacy students perceive and expect learning outcomes accomplished from LA in their education. Ultimately, this can prove better understanding of their future experiences and needs. Further Cohen et al. (2007, p. 137) points out that it is important that the qualitative data contains clear and detailed descriptions so that other researchers themselves can decide if research findings can be transferred to other cases and situations. In an effort to achieve this the analysis aims to give the reader an approach that builds around detailed descriptions, interpretations, and the context they take place, and help the reader feel "invited" in the research process, a notion that is also supported by Lincoln and Guba (1985, p. 125) and Postholm et al. (2018, p. 238).

Even though the concept of reliability in qualitative research is debatable, the research has put effort into taking advantages of well-known and established theoretical and methodological frameworks as means for achieving reliability in this thesis. This being, systematically applying purposive sampling to study a small but precise target group, developing an interview guide suited to participants with pilot interviews, followed Kvale and Brinkmann (2009, p. 118) recommendations in conducting interviews in qualitative research, utilizing Malterud (2012) Systematic text condensation for structured analysis. Finally, this is put in the context of a social-constructive point of view acknowledging that knowledge is something that is constructed between social interactions. Hence, ensuring transparency in every step of the research process is an important part of strengthening reliability in the thesis.

4.7 Ethical considerations

Ethics within research is concerned in how the researcher balances the requirements in professional research and rights of the participants, and regards that scrutinize this process (Cohen et al., 2007, p. 51). The first step was officially having the research included in FREMFARM, a research project funded by "Diku" and "Stiftelsen til fremme av norsk apotekfarmasi". The participants had approved their involvement and participation in FREMFARM, confirmed by Norwegian Centre for Research Data (NSD) and available at RETTE[9]. Following in this study all participants were asked to sign a consent form after they were informed about criteria in the study (e.g., audio recorded interviews, voluntary participation, and withdrawal without penalty) (see APPENDIX 2). The principle of consent is to protect and respect the right to autonomy, and makes some responsibility fall on the participant if research somehow goes wrong (Cohen et al., 2007, p. 52). For example, during the interviews most participants were happy to know that they remained anonymous and could withdraw at any point. All the interviews were recorded and transcribed, and then saved onto a USB drive. The data was anonymized to maintain confidentiality and the participants were informed that the data would be deleted once the FREMFARM project ended.

4.8 Limitations

No research is without limitations. Regarding the interpreting the results of our study, it is important to consider the limitations that apply. When it comes to possible misinterpretation

[9] https://rette.app.uib.no/docs/2.2.0/rette

that can be caused in qualitative research, participants can tend to give answers to ‘satisfy’ the interviewer or portray themselves imprecise to their attitudes. This means that they might give some inaccurate answers. Another source of misinterpretation is caused by the researcher’s translation of the participants’ statements. Although, effort has been made to uphold the integrity of the statements to their true form, some alterations are made to make them ‘more readable’.

This study has had limitations when it comes to sampling and participation size. One way of broadening the findings could have been by including a variety of stakeholders, such as instructors and teachers, or having a mixed method approach measuring (e.g., self-regulation in a standardized test with a Likert scale). Another way could be to measure students’ academic data and activity from online courses in the LMS. When conducting further research on this topic, these approaches should be considered. Another approach to this research would be in broadening the target group, having more participants and bigger sampling size, giving room for a mixed-method or a quantitative approach that is more rigorous, structured, and less flexible. Which is advantageous than the goal is to generalize data, which this thesis with qualitative approach lacks (Postholm & Jacobsen, 2018, p. 99). This could help contextualize findings, giving more structured analysis.

The research involved participants from their first year in pharmacy, which means that their level of familiarity with LA may not be as high as that of students in fields like information technology and these students may have other concerns or interest compared to students from other disciplines. Students from other disciplines may also have more obligated assessments and frequent interaction with digital learning environments, compared to these students that might influence their attitude towards LA.

The participants in the study had limited introduction to LA prior to the interviews, with only a hand-out flyer, a brief oral presentation, and some clarification of concepts provided during the interviews. While some conceptual approaches were introduced during these interactions, students may have struggled to understand them, potentially limiting their perspectives on the topic. As a result, the participants' statements primarily reflect their overall perceptions of LA rather than specific concepts related to it. To gain a better understanding of student opinions on LA, it would be valuable to investigate how their views may be influenced by being introduced to alternative approaches to LA.

This study has been dedicated to expectations from students as they are the main end-user in LA, with the baseline that students are not well represented in the decision-making when implementing LA to educational institutions. Another important end-user is instructors, which share the similarity their perspectives considered in decision-making regarding LA. While students are the primary stakeholders in LA, academic instructors are also important end-users whose opinions on the matter require further investigation.

5. Analysis and Findings

This chapter will present the key findings from the empirical data. Most of the findings will be supported by direct quotes gathered from interviews and with encompassing information that provides context and explanation to clearly indicate the source of the quote. Thus, As mentioned in 4.8 Limitations, the statements presented in this analysis are translated by the researcher. The analysis highlights some of the central themes that where found using 4.5 Data analysis with Systematic Text-Condensation (Malterud, 2012). Furthermore, the theoretical framework provided by the UTAUT model (Venkatesh et al., 2003) was used to interpret some of the findings. The chapter is divided into three parts: (1) Students Digital Learning experience, (2) Data collection and ethical and privacy issues with LA and (3) Thoughts on LA and features. In the first part the UTAUT was utilized effectively as it could provide possible explanations for user behavior. However, in the last two parts the model is less present. Thus, there are made attempts at the end of each chapter to utilize the UTAUT model.

5.1 Students Digital Learning Experience

When exploring students' expectations to LA in their education it is important to see it in the context of the educational landscape of the students. One way of doing this is to explore how students' attitude, acceptance, and usage of already existing digital learning environments. This is important to highlight since they give a contextual background of how they could see and understand LA services and the possible adoption of these features in their educational digital learning environment. This section will look at the "Quality of information", "Usability of LMS" themes and some subthemes that solidified after the systematic text condensation. This chapter of the analysis focuses on how the students experience digital learning environments with focus on their LMS, how they express acceptance in use of different technologies related to their studies, and how they experience current barriers and challenges to digital learning.

5.1.1 Students experience with Learning Management System.

The participants' opinions towards MittUIB are mixed. Ranging from being satisfied to frustrated with what it provides, how it works for them, how and what kind of information is presented to them and the way they use and interact with the user interface. Thus, all the informants have experiences with different LMS being competent when interacting and using these systems in combination to their education. Even if the participants point out that they are experienced with LMSs, they have different opinions when it comes to how well it performs for their needs. They also have different expectations regarding how much effort should be put into the work when using the systems. Participants mention some social factors influencing their use of digital tools in various ways. And lastly pointing out that they are affected by the environment by using different types of digital tools in their education, since they are more facilitated than others. One distinct finding is that they have different experiences and perspectives with digital learning. One participant gives a possible explanation that it might be because students are different and with different interests.

Informant F27

> "[…] Some are very happy with being on the computer all the time, they explore stuff, and they like to see stuff."

This participant underlines what might be one of the most essential things to consider when it comes to experiences with digital tools for education. That students are not homogenous, and that some might be more interested in digital solutions compared to others. The same goes for opinions about digital learning environments such as MittUIB and experienced ease of use.

Informant F27

> "[…] Yeah, I feel that, as long as it's easy. […] If I am at school for example we need it, and that enough doing the same, but if it's a hobby, right? Then the app can be more advanced, because then I want more from it. […] I feel in school, when I go on MittUIB, I only need courses and files, assignment dues and those things. I mean what else should I do there? Should I sleep there?"

So, the participant finds it easy to use MittUIB for school related things such as essential functions of the LMS, further pointing out that the environment delivers what it is supposed to. Additionally, she appreciates more complicated environments when it becomes a hobby or something that she will use in her free time, hence wanting to explore it during free time. This can mean that the participant distinguishes between a personal and recreational digital environment and a school related environment. Furthermore, the participant asks herself what else should one do in more advanced school environments. The participant is compared to the others the one that is most satisfied with MittUIB. While it seems that the younger participants are generally more unsatisfied with the LMS and what it provides. This might be consistent according to UTAUT, that age influences both performance and effort expectancy.

One way of understanding these statements is that the participant has no interest in more advanced features provided by an LMS. Another way is to that the knowledge to the LMS is limited to the "things we need to do", and using or having more advanced features provided is of no interest because the participant is not aware of possible benefits it can offer. This can be related to the performance expectancy in the way that the participant accepts the LMS for delivering what it should, and no additional features are needed. Thus, if an individual has more experience it could result in them having more expectations, since they have other experiences with systems that do things 'better'.

Meaning that individual experiences influence the effort expectancy, where those with digital interest and experienced users are more prone to become frustrated by a system that does not meet expectations. Thus, the participant also points out that if the system becomes a hobby, she would expect more from it, this goes against the UTAUT model, which states that the only influence "Voluntariness of Use" has is on social influence(Venkatesh et al., 2003), while the participant highlights that it also could influences performance expectancy.

> **Informant 1**
> "I got to know this system the last year of high school […] without this I would have been completely lost."

The overall impression is that the participants are experienced with different LMS. Pointing out that experience is vital for the user behavior. Informant 1 goes so far as to say that without this experience she would be "completely lost" and later adding that the perceived impression of the LMS is very confusing. The statement was made in the focus group where the other participants agreed with her statement. This could indicate that experience will LMSs will make operating the system becomes easier but can still be challenging for students. However, the experience alone does not impact the satisfaction of users.

To understand what the participants mean when talking about experience, they often mention two dimensions. One being instructional design, how the learning content is distributed and presented for the students on the LMS and the other being interactional design. For now, we will concentrate on instructional design. The participants utter frustration when it comes to instructional design on the LMS.

> **Informant 2**
> "We have different teachers, that place content on different places, so it is a bit confusing some places, and we have to search for a while before we find what we are searching for."

The statement highlights that instructors are using LMSs in different ways, and might be a explanation for why the participants are finding it hard to navigate when searching for information on the LMS. The participants point out that can be frustrating to navigate in the LMS when announcements, files, modules etc., are used differently by instructors. So, while students are getting more experience with the system. Meaning that they constantly face challenges when using it, because it does not seem that the teachers use a strict framework when using the LMS. Using the UTAUT, one can understand this as effort expectancy, where they must put in more effort adapting to different instructors or as facilitating conditions, where one can see that the students experience constant fluctuation in the environment and impacting them to change and adapt user behavior.

One important factor to identify going forward in this analysis is to perceive how students understand the "Usability of LMS". The exploration and understanding of this could possibly help to gain insight into what students perceive as useful from LA services and features. The concept of usability is a critical factor in determining the success of a product, service, or system. Defined as the ability of specified users to achieve specific goals efficiently and effectively with satisfaction within a particular context of use (Freire et al., 2012), it encompasses the ease of use and learnability of the product. Usability is considered a fundamental aspect of user experience design.

As mentioned, previous the students differentiate between two dimensions when talking about experiences within the LMSs. The first was instructional design, with the other experience dimension is interactional design, which is tightly related to user experience design and concerns creating intuitive and relevant user interfaces facilitating and improving user experience. It includes front-end layouts of interfaces and navigation though the system for the end user. When interviewing the participants, they often mention other systems comparing MittUIB with them.

> **Informant 4**
> “We used ItsLearning, I think that it’s much better. Yeah, and easier as well. Then came Teams, where we got notifications on the phone, then I didn’t have to go through the app to see. As well it was much easier to find things.”

With these statements it can seem that LMSs in general is not the issue, but MittUIB has some core points of frustration for the students. Whereas students compare with prior experiences and remember them as better. Furthermore, both statements were taken from the focus group interview and seeing this related to a group dynamic and social constructivism. One can also reflect on the possibility that participants are enforcing each other’s position and attitude. However, these are interesting findings that pose that the design of MittUIB is causing dissatisfaction during interaction with the system. One informant explains her interaction patter like this:

> **Informant F27**
> “[…] I feel on the internet sometimes, once something is very advanced and complicated, then “no thanks”, we want something that is somewhat easy, right? Especially when it is things we need to know about.”

This implies that the participants want a system that requires little effort. This expectancy is resonated by other participants as well, when they start comparing to experiences gained from other online platforms some being TikTok, Instagram, Messenger and other LMS like ItsLearning, for giving a better user-experience.

> **Informant 1**
> while TikTok. That's where I am. I live there. You just have to scroll there. It is so easy, you see?

These apps are simple and intuitive as they perform to the needs of the user, with minimal effort and are supported by voluntariness of use with viral social influence that facilitate conditions with people and friends creating content. Nevertheless, a LMS is not a social media platform, neither is it trying to be one. This means that can be challenging to meet all expectations that students are expecting when engaging in a digital system like MittUIB.

Having that said, designing systems for the users is important and looking more nuanced in the students' statements there are also more specific things that are impacting the perceived usability of the LMS. As one informant explains, the system must be delicate.

> **Informant F22**
> "It has to be user friendly, if it's not there is no point in... how should I put it, it has to look delicate if one shall bother to use it, and if it doesn't work there is no point to use it."

Delicate is an interesting word, just like a delicate meal, it should look good, be nutritious, have a good reputation and the ingredients should work together in harmony. The same could be said of a delicate learning environment, it should look good and be intuitive, useful, and content-rich, be socially recognized and have a learning ecosystem that facilitates conditions around it. The informant further explains what she does if it's not delicate.

> **Informant F22**
> "Then you spend a long time on it, and you don't even bother, at least I'm like if I can't figure it out, I don't use time on it."

When it comes to deciding factors for the student's digital engagement the participants are pointing out numerous reasons on how they are engaged or disengaged to specific digital systems. They seem to point to well-known apps that have a simplistic design and have straightforward features. Relating to LMS, it must be effective in giving the students what they want. Furthermore, the participants' crucial functions of the LMS are the calendar, course content, announcements, and timetable of deadlines. However, according to the participants these functions are problematic. Furthermore, several participants note that they receive a lot of information from the institution, and it often becomes too much, making information disappear.

> **Informant F22**
> "It's a great ball of information [laughs], but it quickly becomes too much, I feel. In other words, in the beginning, there were so many announcements and e-mails, and er where bombarded and then it disappeared."

Which brings us to another point stressed by the participants. The point is that there is a need for the right information at the right time. The general impression is that MittUIB can be overwhelming at first, being a ball of information that can be challenging to get control over, where information is placed different places and lack of information hierarchy. One can understand this through the UTAUT model that this limits a student's expectancy in performance as they cannot extract the right information effortlessly. They criticize it, then constructing a collective skepticism, lowering a positive social influence. Thus, an interesting find from an informant F27 that regularly visited MittUIB and had overall mild satisfaction with the LMS. Despite being aware that there are fellow students expressing frustration against the LMS.

> **Informant F27**
> "The thing is that most of us are hating on it […] a lot, sometimes as well, you lose what you should read, but apart from that MittUIB is quite.., in a way, how should I put it, nice in a way, tidy."

This statement is interesting since the participant refers to the hate towards MittUIB as a collective thing, something that is socially constructed between peers. Especially when losing what you search for on the LMS. Also indicating that social influence might not affect every individual as much. Then continues to state a more individual declaration of it being nice and tidy. One way of interpreting this is by seeing some of the frustration towards MittUIB being socially constructed between students. This can also be found in UTAUT where "social influence" is a key factor indicating user behavior. Nonetheless, there are four key factors in the UTAUT, meaning that this collective frustration towards MittUIB can only partly be blamed on social influence by teachers and fellow students.

5.1.2 Barriers faced while using the system.

From the empirical data we find some key challenges and barriers that seem to impact the experience. When looking at issues and barriers they have gained from experience, one can interpret it as a way that they have expectations for the system to behave in another way than it does. Barriers and challenges can therefore be important in pinpointing what is important for the students in existing and new digital learning environments or features (e.g., such as LA). In the previous chapters we have looked at general experience and mentioned several challenges students face while engaging and interacting with the LMS. One challenge is that they face an overflow of information when engaging in systems, causing them to avoid interaction with the system. As the participants utter frustration with tricky navigation though overflow of information, there is a need for quality. “Quality of Information”, as students are given information from different sites, and different instructional designs, which cause confusion and frustration. The importance of a universal structure that is reliable can therefore be important to make students feel at ease when attending different courses in the digital learning environment. This also means that any new form of information, such as LA must consist of features that are necessary for the participants. This might be because the students have limited patience and time engaging in digital learning environments, stressing the importance of systems to deliver performance efficient information that require little effort to comprehend and understand.

Another barrier is the social influence and facilitating conditions that participants point out in MittUIB. As seen from the different participants, they explain teachers are asking students to communicate with them through mail instead of using the message system provided from the LMS.

> **Informant F22**
> “Yeah, they don’t want it on MittUIB, because it has something to do with that you can’t reply on a message in MittUIB from email.”

This could be because the teachers and students find it more practical or are leaning towards a more traditional form of communication to communicate through mail, and a software that is available both on all their digital devices. Another interpretation could be that it could explain that they are less familiar with the LMS and usage of the messaging system. Either way it emphasizes the need for management and guidance in utilizing a broader range of functions within the LMS to increase engagement. Thus, this might not voluntarily it will over time become routine, and students and teachers will become dependent on such systems, rather than having too many options from different digital tools. Another participant comment highlights that the university has taken measures into account and tried to promote some degree of mandatory use of MittUIB.

> **Informant F22**

“[…] we have a mentoring arrangement, so they have both MittUIB page, because the university wanted them to have one, so they must add information there and then they have a Facebook page there they post the same information because that's where people are.”

And further adding that the students have taken countermeasures and created a group on Facebook posting the same information. Indicating that they have applied voluntariness of use of another system just to avoid MittUIB. Using the UTAUT model, we find that voluntariness is influenced by social influence and makes sense in this context. In addition, the students are adding more workload to their plate just to reach out to all students, since they know MittUIB is not used. One participant explains that mandatory obligations can have a negative impact on mental health.

Informant 1

“I don't like mandatory, I'd rather, like then it becomes more like anxiety and stuff to log in there […]

So, the usage of mandatory engagement is Janus-faced, where it on one side can have positive impact on students’ activity on the learning platform forcing them to complete assignments and engage with features. On the other side, students can end up feeling overwhelmed and potentially resulting in decreasing enjoyment during their studies. Mandatory commitment forces students to use time on one way of learning. Hence, it can also limit students that wish to use their study time to acquire knowledge from alternative methods.

Furthermore, findings show that they have different experiences with digital environments and expectations of what they should and can provide. The UTAUT model has four moderating effects that haven’t been mentioned so far in this analysis. These are gender, age, experience, and voluntariness of use. Each have effect on one or more of the key factors. As this is a small qualitative study could not give profound evidence of this being the case, thus some indication that they could have an influence.

With the emphasis of moderating effect ‘age’ (Venkatesh et al., 2003), We find on the one hand that the oldest participant is the most accepting towards their current LMS. Describing it as a nice system that does what it should. Further the participant notes that her performance and effort expectancies are not that high. On the other hand, the younger portion of participants had higher expectations towards performance of the LMS, this was interpreted by the participants frustration towards challenges and issues with navigation, design and in what beneficial way it could perform for them. Furthermore, some expected that they would need to put much too little effort into engaging in the system. The data did not show that age had any impact on social influence of facilitating conditions given findings in the empirical data.

exploring the moderating effect of 'experience' the participants point out on several occasions during the interview the importance of experience with digital systems. Meaning that the participants stated that general experience with digital systems had an impact on their ease of use with LMS and other digital environments influencing their user behavior. The experience was stated by some participants as crucial to use the LMS effectively. Furthermore, the participants show awareness around other students' attitude and experiences with digital systems but are not directly pointing out if this is influencing their behavioral intention, thus one can make some assumptions that this might be the case. Lastly the students point out by experience that teachers are not actively promoting the use of LMS, and they are using different instructional designs when delivering courses, causing frustration and confusion for the participants. This hints at the facilitating conditions factor from the UTAUT model as an influential element for participants behavioral intention in the LMS.

Lastly analyzing the empirical data, some evidence that the last monitoring effect 'voluntariness of use' had influence on the participants user behavior. In the UTAUT model Venkatesh et al. (2003) states that voluntariness of use only has impact on social influence. However, findings show that it also impacted performance and facilitating conditions. This became evident when some of the participants pointed out that they would engage more in the system if it was enjoyable and became more of a hobby. Yet, voluntariness is hard to determine when it comes to a LMS in an educational setting, where students are expected to engage in the system to follow the study program and achieve intended learning outcomes. Denoting that these assumptions made are more speculative compared to the other influential elements that are pointed out in the analysis above.

Summarizing this chapter, we have looked at the participants' current experience of LMS, and how it is influenced by a myriad of issues and challenges. These are important when understanding expectations students must LMS. As they can be compared and maybe avoided when implementing similar or new digital systems in similar contexts. With the help of the UTAUT model there is evidence that MittUIB falls short in living up to the expectancy of students and that both key factors and moderating effects should be considered when developing LA technology that has the goal of successful implementation and functionality in an educational setting.

5.2 Data collection and ethical and privacy issues with LA

This section will address ethical and privacy points of view that emerged from the systematic text condensation. The central themes used in this sub-chapter are “Data Awareness”, “Use of personal data” and “Determined by Numbers”. The last section of this chapter will address how the UTAUT model can be seen in relation to findings in this chapter. To provide transparency in the research process it is worth noting that LA technology is new to the students, and some of the students seem to relate LA primarily to data gathering to privacy and ethical concerns at first. During the interview aligned knowledge was socially constructed between interviewer and informant.

5.2.1 Students knowledge and awareness of data gathering and analysis.

An important step in understanding students’ expectancy was to map out how students identify data and what construction of knowledge they have of data gathering. Hence “Data Awareness” theme that emerged from systematic text-condensation. To tackle this challenge, a series of questions asking how they understood data gathering and generalized questions on how they understood personalized commercials that they face when using online services. Findings where there is a wide variety when it comes to how this process happens. Some participants show less knowledge and awareness,

> **Informant F27**
> “It happens often, and it makes me think, omg, they are in my thoughts, like it happens, but I don’t know why.”

And others are more aware of the collection and analysis of personal data.

> **Informant M22**
> “In my assumption, it will be based on the websites you are on and the cookies they collect. Yes, so that mainly, maybe there are more conspiratorial things you can do as well.”

Thus, all participants are aware that some sort of data gathering is happening when they are using digital systems. As we see from the participants’ comments there is a large span between in how detailed they understand how the process of using data to personalize content for user based on cookies[10]. This span emphasizes the importance of informative and clear communication when informing users when it comes to data usage. As some students have a clear understanding of how their data is being used, others might be unsure or unaware that can result with them sharing personal information that they did not know existed. The variance also points out that students are not a homogenous group when it comes to this matter, stressing the importance that the communication should be personalized to meet each student's level of comprehension and knowledge. Interestingly, some participants were surprised to find out that MittUIB also gathered cookies from users, even if they showed awareness and knowledge to cookies.

Informant F22

"Does MittUIB use such cookies and such? we don't exactly get public advertising."

This raises questions about how students experience the level of transparency when it comes to their data collection practices. Furthermore, students note that they are mostly unaware of this happening. Thus, after further asking into the matter some participants tell have stories where teachers have used activity data to determine if been active or done homework. Implying some degree of knowledge that their digital traces can be tracked.

5.2.2 Ethical and privacy concerns related to personal- and activity data.

When using LA as a tool for analyzing and interpreting it requires access to learners' personal data, such as academic performance, personal information, and digital activity. With extraction and use of such data there are ethical and privacy concerns that need to be considered. As presented in the previous chapter, there is a large variation to awareness and knowledge when considering "Use of Personal Data" theme found in the analysis related to storing and usage of data. The individual differences are also present when it comes to privacy and ethics of data. Stressing the importance of transparency and guidance to personalized instruction on the matter. In the beginning of this study privacy and ethical concerns had little intention of focusing on privacy and ethics, but students focus on this topic was present and mentioned by the participants, underlining that it cannot be ignored in this thesis. When talking to the participants every student had an opinion related to privacy or ethical concerns.

Informant F22

[10] https://www.datatilsynet.no/personvern-pa-ulike-omrader/internett-og-apper/cookies/

[…] In that case you feel watched, but who cares? I mean who should be interested? It is in a way yes, but yes it is perhaps a bit naive?

So, the participants note that they feel watched when it is brought to attention that data is stored on them while using MittUIB. As seen above, this informant does not seem to care, but also adds that she might be a bit naive. At the same time, other participants are more mixed, one participant does not mind sharing educational data, but it might depend on what kind of data. Which could mean that the informant is more restricted in sharing sensitive data.

Informant M22

"It doesn't mean that much. It's not like anything special is happening. Unless it's held against me […] Hmmm it might depend on what information they want."

Informant F27

"You can't trust them 100%. [...] everyone is very good, but you also hear thousand cases about the professors and students, don't you? Imagine if someone used the data in a bad way."

While some find it straight out creepy knowing that teachers have access to log data. The greatest fear is that some of the participants are expressing is the potential that their data can be misused by someone. It is not necessary based on mistrust in teachers, but the potential and the thought of personal data in the hands of someone else. One might interpret that the informant is talking about the privacy of special categories of personal data, which includes sensitive information that might be identifiable. However, the boundary that the one participant describes as personal data being misused might argue otherwise.

Informant F22

"I know that at a high school there was a teacher who used it as an absence if you had been in and checked a message […] if you have opened a message or something like that and then it had been used as absence or not delivered. […] in that sense it's being abused, I'd say."

In other words, the teacher had used students' activity data to see if the students had "seen" the post, those students that had seen it and not completed the task were penalized. It is interesting that the participant describes this as misuse of power, as it is quite a normal practice for teachers to work in this manner in a normal classroom. This brings us to a more ethical approach when it comes to consideration of data. Ethics within data usage relate to transparency and responsible use of data. So, even if it is a normal practice in a classroom, such practices in digital spaces are uncommon, and students might not be informed or expecting these types of surveillance. Hence, underlining the importance of transparency when executing acts based on data. Responsible use is pointed out above with that should not be misused. Several participants suggested that the data could be handled by others, so the data could not be used against them, and maybe cause less biased assumptions. Furthermore, the participant made an interesting comment reflecting on making decisions based on numbers.

> **Informant F27**
> "It's more like this "What am I, a human?" get it? Regardless, the feeling changes all the time […] Occasionally it may be wrong, and it could impact me negatively."

Here the informant dwells on how far data can go in understanding her as a human. Furthermore, reflecting on how we can be converted into numbers. While not explicit, several other participants mention similar concerns creating the theme "Determined by Numbers". This relates to the challenges of identity in the age of information, as we may increase to base assumptions on data and algorithms. Personalized analysis can be inaccurate and have a great impact and have both negative and positive consequences on individuals. This can mean that there important to treat LA as a tool among others when shaping data points about individuals. One informant believes that it is possible to provide useful analysis from students' data that can be useful.

> **Informant M22**
> "I would think it would be technologically possible, but there are certainly ethical questions that arise in such operations."

While it may be technologically possible to collect and provide a useful analysis for the participant, the informant suggests that it involves ethical considerations while doing so. A possible concern related to accepting the conditions of having LA integrated in their education, is according to the participants the fear of being turned into a number.

> **Informant F23**

"It can give the wrong impression, in how you study if they just look at some numbers."

The unease of being turned into a number can cause different types of challenges and outcomes, according to the students. One of the concerns is that it can cause discrimination towards students and make decisions from data points putting students in boxes.

Informant F22

"You can be put in a box because they already know a lot about you."

The students later explain how this is already practiced in their chemistry class, where they had a test in the beginning of the semester checking how the student's prior knowledge. This was anonymous. While this can be good for designing the course to fit each student, it can also put them in boxes limiting some student's potential to learn and grow. This approach resembles both descriptive LA and can give valuable data for both instructors and learners. However, if predictions are wrong, it can restrict or limit students' learning. A way of avoiding this is by making sure handling such data should not solely by algorithms, but with careful inspection from teachers and instructors with pedagogical or other theoretical framework. Further highlighting the previous chapter in ensuring that data collection and analysis is used for its' intended purpose, and that students are not subjected to any negative consequences.

Informant F27

"As long as it helps me, then I don't think so."

Further, one of the informants commented "as long as it helps me". This resonated with what several of the participants point. That they will comply with the requirements if it can give them a positive impact on their learning experience and outcome. So, from talking to the participants it seems that they are accepting this cost-benefit situation. Creating a trade-off paradox, where they might have to sacrifice some personal information to have personalized experiences online. One participant points out this specifically.

Informant F22

"There will be that kind of control management again and we don't want that that. [...] but it is perhaps difficult to get one without getting the other somehow."

And they seem positive to the possible impact it could have on their education, if the data is used in a manner that complies with their ethical and privacy expectations. Thus, they need to accept that this can cause data analysis to determine control management over the students learning and outcome. Furthermore, some participants mention that this control management could be helpful for teachers, where they gain quick access to information to students that could support them in effective decision-making and maybe have more time individualized follow-up on student needs.

Another interesting finding was that some of the participants are reflecting on how valid formal decisions made by teachers on personal data. One participant mentions that students have individual learning styles, meaning that data will have great variation. Therefore, it can give the wrong impression when students are not producing the "right" type or amount of activity data to satisfy the algorithm or learning theories implemented in the analysis of the personal data.

> **Informant F23**
> "[…] Then they can get the wrong impression on how you study, if you only look at someone as numbers, but it could be alright if it was written. "

So, the informant is uncomfortable with the idea that increased use of data analysis could turn them into numbers, which is in accordance with the attitudes of most of the other participants. With the social influence principle in mind from the UTAUT model one can reflect on how they can be socially affected by knowing that they are observed in their activities. Ultimately, this can result in alternation of behavior in an unnatural way just to satisfy the data analysis. Some of the participants reflect on this scheme when they are made aware that teachers can see how many times, they are visiting pages on courses on the LMS and saying they need to be "more active" to satisfy the data. The informant also mentions that it would be alright if it was written, by this she meant that if data was only descriptive and not used for formal decision-making it would be alright and even helpful for self-observation during learning and studying. This help could increase students' performance and effort expectancy towards online learning environments as they might have a tool to observe their learning and alter their behavior accordingly to meet their personal goals. Using the UTAUT model we can explain this from fulfilling facilitating conditions and social influence in a system. If they are met it will have a positive impact on students' behavior in the system. In other words, where data is managed according to their preferences and used to improve the learning environment in different ways.

5.3 Use of Learning Analytics and thoughts on features

When approaching the question on how students expect LA to influence their educational and learning practices, meaning that exploring how the students would like the data and analysis presented to them and how it can impact their engagement, motivation and learning strategies. Two main themes that emerged from the analysis were "LA, help or hindrance to learning?" and "Usage of LA". Since most participants were uncertain of what LA technology was, the interviewer had to assist the participants with concrete examples of data generated by students that could be relevant to them and how descriptive and predictive analyzes could work. In other cases, students themselves were able to connect other analytic features from other systems, suggesting them as LA features assisting their studies.

5.3.1 Believed and ideal impact LA might have on education and learning.

As noted in 1.3 Previous Research, research points out that LA can impact students' way of learning and influence their educational degree in numerous ways. Thus, LA requires students' data to be collected, stored, analyzed, and presented, the students need to give up their data to make it all happen. In the last chapter some key statements were highlighted, shining light on how students are reflecting on privacy and ethical considerations in sharing data. In this chapter we look at how participants think LA features and services can influence their studies and education.

The students seem to have different experiences with assisting digital systems and software. Therefore, this results in different social-constructed expectations in what is defined as 'help' from digital platforms and alternatively from LA. One participant suggests that the LA could give recommendations on relevant academic articles based on personal data, to fill gaps or supplement current knowledge.

> **Informant F22**
>
> "Alternatively, it could find relevant articles and stuff, but I can't quite see how."

The participant has experienced this recommendation feature several places when using Web 3.0 and is aware that it is based upon previous activity, the same goes for the other participants. The reason the student does not understand how this could be done in the context of the LMS or from her education is that the participant rarely engages in learning activities on the LMS or any other digital software provided by the institution. However, the participants are positive to tools that can help them analyze and observe their own learning. According to several participants it can help them to see their progress compared to what is expected from them. Additionally, one participant mentions that this could be helpful for students that are behind, to see that they need to put in extra effort.

Informant F27

> "It might actually help those who struggle, […] that can be helpful and become a little Better, so that we all can finish more equal."

Interestingly the same participant mentions that assisting students that struggle with LA feedback could lift those students, making sure they are on the same knowledge level as the rest of the students. LA can provide substantial assistance to students that are behind, with recommendations and progress tracking. One participant reflected on how this could impact herself or other students.

Informant F22

> "[…] either you become more motivated and want to learn it, or if you always fall short no matter how much you work, you may not bother anymore, I feel I may be at the latter."

Pointing out that personal awareness of progress in a course can have two possible outcomes, further mentioning that it could impact her negatively. Hence, it can be overwhelming to students to be reminded that they are behind on curriculum, and it really comes down to individuals' behavioral patterns when getting feedback. This last reflection is also mentioned by an informant. Additionally, some of the participants are pointing out that it is important that the feedback is precise and accurate, as they are already flooded with huge amounts of information when entering a digital learning environment. This brings us back to the importance of quality of information, as mentioned in **Error! Reference source not found.**.

Informant F22

> "It's good enough that you can take a quiz and then get an analysis, but if you don't understand what you're going to use it for, it doesn't help."

So, when getting any type of LA feedback it needs to be recognized as related, relevant, or useful for the students to impact the students in a positive way. Unless this is the case, the participants seem to be negative to such kind of features. This point of view might come from experience with other platforms. As they have strong attitudes against too much information. This approach is stated as preferable by several of the participants, compared to feedback that constantly gives feedback that can cause information overflow and fatigue.

> **Informant F22**
> “As long as it doesn't become too much [...] Being overwhelmed by it in a way so that you disappear in the information-flow in a way, but also if you have much focus on it all the time, you might become completely overloaded. instead of taking it at your own pace or sort of accepting it or doing it your way.”

Interestingly the student reflects on the idea that LA services could provide too much information for the learner, where you end up fully focusing on the information received by the analysis causing information overload. Further, adding that the alternative is taking the learning process at your own pace this relates to the theme “LA, help or hindrance to learning?”. As one way of interpreting what the informant is trying to say is that learners might get dependable on the services of LA causing them to follow instructions according to the feedback the analysis gives. Where the alternative is finding your own way of learning without instructions, finding your own way. When students receive personalized content based on their data it should ideally recommend information that is perceived as useful for them. One student note that this can also cause challenges based on her experiences, where the predictions made give more content on things she is interested in, that she already knows or could have come up with herself.

> **Informant F22**
> “So it is that you "miss out" a bit on other things when that is the only thing what comes up, in a way, that one misses the width that they might have gained, like "Oi. I may be interested in this, but yes, you know, I could have come up with it myself in a way.”

When interpreting the statement, it seems that the informant is pointing out a potential downside of LA if it is based too heavily on data-driven decision making and could possibly be a hindrance for independent learning. The participant is basing it on how pervious experiences with commercials are on Instagram being too repetitive and based on reminding users of what they are interested in, rather than predicting. While LA can provide help identify and improve and measure students, the participants note that it can give a narrow focus limiting students in exploring content in a more “natural” way. A possible conclusion from these statements is that some participants tend to lean towards preferences in encountering new content themselves, rather than following algorithms that do the work for them. Implying that LA could be an effective tool, but rather replacing the process of obtaining knowledge, it should not replace or limit users’ curiosity when engaging with learning content.

Interestingly one participant mentions another reflected concern when it comes to how LA could impact learning and education. The informant mentions that descriptive LA could limit him in self-exploring his own learning and refers to the knowledge prosses that learners face when exploring, evaluating, and selecting learning material to match intended learning outcome.

> **Informant M22**
> “Depends on what the knowledge process is. […] I think the knowledge process includes the whole process of understanding learning in a way. “

One way of interpreting this is that the participant is reflecting on how LA services would assist him during the course, but simultaneously remove some important elements that learners are confronted with when engaging in learning activities. A consequence of this could be that the informant might lose parts of important steps to acquire knowledge and become dependable on such LA services to learn in the future. This reflection goes beyond the UTAUT model with performance and effort efficiency, where the informant is reflecting that LA services could make learners so dependent that they need to engage to achieve efficient learning.

As seen above the students have experience and ideas of how this happens from other digital platforms. Thus, some students talk about “a page” or an overview where they can see their personal analysis. One participant even mentions “end of game stats” where he refers to a summary score after playing a videogame. One participant hopes and believes she would use LA dashboards to observe her personalized analysis. Interestingly, she reflects on that they should be specific, and comparing it to learning objectives that each course already provides.

> **Informant F22**
> I hope and believe that I would observe it, yes in a way, and could take advantage of it and [...] specific things, it is all the easier to make use of it.

Meaning that the informant is looking for feedback from LA that is specific and not generalized. So, the idea of an LA dashboard does not seem to be totally new to all the participants. Findings from the interviews point towards that the participants are positive to such LA dashboards but are not sure if they will use them because it will something new and unfamiliar to learn. So, unless LA dashboards have ‘proven’ effect on their learning they do not seem to be interested in using it themselves but adding that they can see that it could be useful for learning about their own learning. According to the participants, there are several ways to provide this to the students, there are different opinions on how they want the data presented to them. This also points out students expectations “Usage of LA” A common way to present and illustrate data is by showing graphs, one participant specifically mentions graphs as a bad idea to illustrate her personal LA.

Informant F27

“I don't like graphs I have enough graphs. […] Maybe drawings, I don't know…”

Interestingly, the participants talk about drawings, or story board with acting. This might imply that the participant wants the data presented in a more creative illustrative way, rather than having precise classical data representations. Another informant points out that LA should be presented with extra information on why they are seeing the specific data. With the example that they are learning this specific chapter in chemistry because it is relevant for the next course you are taking. Coherence between courses in education is important, and LA feedback could possibly mention this during digital learning sessions. In addition, one participant mentions that the type of wanted LA feedback can be influenced by the end goal of the learner.

Informant F22

“To have a future goal, instead of just preparing to perform well in the exam, it is very individual how people prepare.”

Meaning that individual learning styles and preferences will impact what they need. As some might need recommended articles that they can read before an exam, others might want quizzes or dashboards that provide analysis of their learning, or some prefer no interruptions from digital systems. Using the UTAUT model all the four main determinators for user behavior are relevant here, since they in one way or another can impact performance, efficiency, social influence and facilitating conditions. This will be elaborated further in the discussion chapter.

Some of the participants mention using YouTube as an alternative way to obtain knowledge in chemistry, as there are many good channels that explain composition, structure, properties and change of matter. After watching a video YouTube often recommends related topics that students find helpful, but also can be distracting when it is not related to their related learning outcome. On one hand the participants value alternative ways of obtaining knowledge, where they engage in a platform such as YouTube, Kognity or discussion forums rather than using traditional textbooks. Kognity is mentioned by one of the participants as an enjoyable learning platform that utilizes LA and AI principles when providing customized learning for the user. The participant that had experience with this platform appreciated the versatility of features and as a tool for learning. In addition, the participant points out that it gives freedom to the learner, making it possible to learn the style and pace they prefer.

> **Informant F23**
> "Kognity, with quizzes, tests, and everything. It was very nice because you had so much, and you could practice. […] you can work on what you want, not what the teachers just give you as assignments."

On the other hand, some of the participants are avoiding these possibilities, and concentrate rather engaging in the given curriculum in the specific course. Those who concentrate on the curriculum say it is because they do not want to get distracted by too much or irrelevant information. Either way, some features of LA can give a more customized learning environment to suit each student's need and possibly increase motivation. Thus, some students are aware that such extra features such as recommendations can be distracting for the learning. This boils down to the need for digital tools such as LA must be adjustable to fit every student's needs. Moreover, several participants point out that LA services could impact the students in pace and tempo in achieve learning outcomes. Thus, customized learning could challenge collaborative learning as students are on different levels in the course.

> **Informant F22**
> "You get a more challenging syllabus because you are good in this subject somehow? Yes, it will probably be based on the individual, but it is difficult to work in a team in a way."

The informant is concerned that if students have access to too much personalized learning material it will be hard to collaborate both online and in classes. This might be the case if the goal is to collectively solve tasks together without giving opportunity to teach and learn from each other. Having this approach can contradictorily give students with different or broad skill levels the possibility to learn from each other if the education facilitates these activities. Furthermore, in higher education the students have responsibility for their own learning, so one participant points out that LA services that customize tasks and curriculum could be more useful at lower levels of education.

> **Informant F22**
> "At university level, you have responsibility for your own learning, I mean in K12 or high school you get more systematic supervision. So, there it could be used to provide customized education."

Informant F22 also points out that LA features can be helpful for teachers, as they often have a lot of students under their care, and limited time to concentrate on student's needs. LA could therefore help in observing students effectively and with less effort. With a good implemented analytical tool that LA can provide it can provide performance efficiency for teachers. One informant points out that teachers having access to their data could help observe students' progress. The conversation is about below is about how LA from quiz data can be useful for students to see, to determine what topic or chapter they need to work more on according to the performance on the test.

> **Informant F23**
> "Maybe they can show me that you need a little more with this one, you can do this chapter but a little more on this one."

The use of data and analysis techniques provided by LA can help to understand and improve learning and learning environment. These include personalized learning, observing student engagement, helping students adapt their learning paths and in some cases taking advantage of predictive analysis to determine students' future performance. From the data material different findings were explored related to how LA could make students studies easier or work as a learning enhancing tool. When referring to easier, the participants give several examples like different tasks becoming less time consuming, such as organizing time used to study, observing, and exploring learning progression, and finding suggesting new content. Lastly one informant reflects how making certain tasks easier could remove important ingredients of the learning progress.

Using the UTAUT model we can understand the findings from this analysis in different ways. As shown in 5.1 Students Digital Learning Experience UTAUT can provide a substantial understanding of students' experiences with online learning environments. Similarly, can be done when understanding how different key factors impacts users' behaviors towards acceptance of LA. Performance expectancy towards use and implementation of LA is found to be relatively high since the participants believe that LA can assist them in their learning process and could possibly improve their learning outcomes. When it comes to effort expectancy the students are concerned that LA technology will take up more time from their already tight schedule and are concerned that it could possibly become mandatory to use. They believe LADs can be useful, but that the data analysis might be irrelevant and not being used. The participants mention that they might be impacted by social influence if they are aware of being tracked, and that they might use a system to satisfy personal data collection. Lastly, they believe that LA can encourage use of the technological tools if they prove beneficial for them, giving accurate descriptions and predictions. Furthermore, it is important that they fit the needs of the participant.

6 Discussion

This thesis has explored Norwegian first-year pharmacy students at the university of Bergen using a qualitative research approach. With the social constructivism approach, we can assume that the students' knowledge around LA grew as the interviews went on. This happened when students were provided with further information and time for reflection. Furthermore, this might have resulted in students conjuring more complex attitudes and expectations of LA based on their experiences from previous education and other digital environments. The study has aimed to unveil general expectations towards LA, but also specific attitudes towards how LA services and features might affect the students at an individual level and in their education and learning activities. The discussion is divided into three sub-chapters, each with the goal to examine the three parts of the research question presented in 1.1 Research question.

6.1 How can students' experiences with LMS be translated to LA implementation?

When exploring students' expectations to LA the goal is to find important insight into how students view and expect from such services and features in digital learning environments. The two central themes that will be addressed and discussed in this chapter is “Usability of LMS” and “Quality of information”. This will provide information to researchers with attitudes and needs from end-users, which can have an important impact on implementation and effectively adopt LA interventions that are facilitated to the student’s needs.

Findings from the analysis discover that students’ experiences can give valuable insight into effectiveness of the learning process, acceptance and expectations towards digital systems and what is important for them in a system for them to using it actively. With actively utilizing the UTAUT model (Venkatesh et al., 2003) the analysis found that performance and effort expectancy is crucial as they engage in LMS with the intent of extracting the information they are looking for fast, and without complications. In other words, if there is too much information or the navigation is too complex, they tend to avoid spending too much time and have less enjoyment with the system. However, the participants cannot be treated as a homogenous group when it comes to these opinions.

LMS has become an important part of academic institutions. The software facilitates and delivers educational content for students, administration and help monitor courses. LMS provides a crucial tool for institutions with its benefits. Thus, it has limitations when it comes to understanding student’s learning experiences (Phan et al., 2022). LA could potentially help with bridging this gap as it can give valuable insight into students learning performance and experience, giving personalized feedback, tasks, and learning content. To successfully implement functional LA services into LMS and other educational digital learning environments, it is essential to understand students’ experiences with those systems.

The participants have a good amount of experience with LMS and have experience in determining the “Usability of LMS”. One important factor to identify going forward is to understand the theme “Usability of LMS”. The exploration and understanding of this could possibly help to gain insight into what students perceive as useful from LA services and features. The concept of usability is a critical factor in determining the success of a product, service, or system. Defined as the ability of specified users to achieve specific goals efficiently and effectively with satisfaction within a particular context of use (Freire et al., 2012), it encompasses the ease of use and learnability of the product. Usability is considered a fundamental aspect of user experience design. When it comes to usability, the informants are using the LMS to reach specific goals, but the efficiency is often staggered by unintuitive user-interface and teachers using the LMS in different ways causing confusion. If we put this into a context of LA usability is crucial for acceptance of such technologies.

Based on this analysis and results from several studies the practical use of LMS in higher education has undoubtfully many successful and less successful features (Alhazmi et al., 2021; Back et al., 2016; Zanjani et al., 2016). The analysis proposes that there are different opinions on the effectiveness of the built-in tools within LMS. The participants statements point out that the primary use of LMS is accessing study information such as lectures notes, preparation for lectures and calendar. Back et al. (2016) found similar results with an exception with the use of calendar. Analysis in this thesis the participants had issues using the calendar but were dependent on using it to follow courses. The reason for this might be that teachers and instructors were actively updating and using it. Furthermore, similar to findings in this thesis Back et al. (2016) found that students did not use the LMS for communication with fellow students or teachers and that students. Additionally, Back et al. (2016) found that students value other sources such as Wikipedia to support efficient online learning. Similar statements were made by the participants that they are looking for external platforms providing them those wanted features and services to supplement their studies (e.g., Quizzlet, Studocu, Youtube, Forum, Outlook, Facebook and Messenger etc). This behavior is challenging the LMS engagement and causing the means for students' expectancy of the LMS and engagement to drastically go down. This confusion is not necessarily caused by teachers and instructors, but also in what functionality the LMS has and what laws limits institutions in using services that can potentially put students' personal data at risk. This can be seen as an important behavioral trait by students when implementing LA services. Meaning that students are using LMSs for specific things, even though it offers additional features already.

Indicating that LA services might become something that will be overlooked by students. Such indications are important before implementing new tools or features in a system and highlights the necessity of understanding students expectations and acceptance of a system (Brown et al., 2014; Davis & Venkatesh, 2004). Furthermore, this stresses how important it is that LA services are developed with students as main stakeholders (Viberg et al., 2022) and that they are part of the decision-making process when developing these tools to find what performance and effort expectancy is wanted by them. Thus, students are rarely included in the process (Roberts et al., 2017) and that can have potential negative consequences towards students acceptance of LA functionality when implemented. Yet, this might not come as a surprise as lack of student engagement, co-creation and development of instructional design is not uncommon. According to Bovill et al. (2011) having students as co-creators in course design and curriculum is recommended, it is seldom used as an approach in the higher education sector as a general.

Another important theme is the “Quality of Information”. This refers to the amount and quality that students receive on digital learning platforms. Based on findings from this study students are sensitive to information overload and information should be given with care. There are several instances when the informants mention the flow of information on the LMS. This information is everything from the user-interface, notifications and all the way to course material. Most of the participants seem to perceive it as unorganized as teachers and instructors are using the LMS in different ways. Putting these experiences in an context with LA it implies that LA should be delivered as subtle as possible and contain information that students can understand and presented to them in familiar interfaces. Jivet et al. (2018) points out that the effect of LA might be limited to students since they might struggle interpreting the data analysis. This emphasizes the importance of teachers helping students understand the LA reports they are given. However, this can be a challenge given teachers different practices, this can cause confusing situations for students. Further stressing that there might be a need for universal guidelines for teachers and instructors when using digital learning environments like LMS and digital learning tools such as LA. Similar statements were given by statements from the students that wanted more consistency in the LMS course material and interface so that they could find and get to various components without difficulty.

Additionally, the flow of information can be too frequent causing information overload. Some informants point out that when facing information overload, they tend to see the information as less important, or in some cases choose to ignore the information. This highlights the significance of ease to use in the LMS. Furthermore, participants stressed the necessity of having a user-friendly and easy-to-navigate LMS, with instructions that are easy to understand and follow. This discovery can be translated directly to students’ expectations of LA technologies. Similar results can be found Park and Jo (2015) study were students perceived the use of a LAD as beneficial, given the design. Thus, students did not find the find the LAD to be easy to use and understand.

Findings from the analysis show that their current LMS is failing to engage students for several reasons. To fulfill students’ expectations, students ask for improved and consistent instructional and interactional design and active usage of the LMS. This might also imply that there is need for instructions and teaching in usage and management of such systems. To increase engagement some participants, point out that mandatory engagement might be required. However, this might impact students’ engagement negatively, ultimately making them avoid the system all together, suggesting that LA technology should avoid having mandatory engagement.

Further these findings are useful when trying to figure out exactly what is important for them in digital environments and what causes issues. When students are dissatisfied with something one can interpret it as they have an expectation of the current issue being done differently. Using the UTAUT model and the framework it provides of analyzing acceptance towards technology, it was found that especially the need for something that is perceived as useful, and it should deliver what it promises. These promises should be guided and consider differentiation in individuals and their prior experience and knowledge. Participants also emphasis having structured guidelines and standardized ways of using the system, so that students do not have to adapt to different ways of carrying out a task. Further carefully design the user interface being delicate, intuitive, and not too challenging for the individual. Lastly having everyone using and engaging in a system can alter social influence in a positive turn, slowly collectively changing opinions. Resolving or partly finding solutions to these issues, can change users' behavioral intention and ultimately behavior. Taking these experiences and using the UTAUT model to interpret them, one can see that the participants experience with digital learning environments such as LMSs can be useful for understanding the expectations towards learning technologies such as LA.

6.2 Privacy and ethics do students expected to emerge with LA implementation.

Findings from the analysis found that students have expectations related to privacy and ethical issues related to LA implementation in digital learning environments. These are related to main themes found in the analysis "Data Awareness", "Use of personal data" and "Determined by Numbers". However, there was a divide between the participants when it came to treating their academical and educational data as sensitive data. In other words, some saw their data as private, and others cared less.

One sub-goal in this study was to explore how students are accepting conditions that LA requires to function, being collection and use of data for analysis. Related to "Data Awareness" participants are uncertain and unaware about data collection and usage in their educational environments. Some students have awareness, but the lack of knowledge extends towards different types of data that is gathered by the LMS and the university. An example being that teachers and instructors can see students page visits and another example that they are unaware of give permission to institutions using their data for analytical purposes in the LMS. Although, these findings might not come as a surprise since LA is still at an early stage in the pharmacy education at the University of Bergen. This finding align with previous research that students are uninformed or uncertain of usage of personal data and LA (Fisher et al., 2014; Roberts et al., 2016a). However, this study found that after a while during the interviews the participants had time to reflect on the matter, they were able to raise concerned about their privacy in digital learning environments and ethical dilemmas fostered by data collection and analysis of this data. Some concerns are that they are worried that personal data might be misused by teachers or institutions, or used to evaluate performance that might be biased or unfair in formal decision making such as grading.

Data collection and usage for LA seem to challenge the concept of students' consent, specifically regarding collection and use of special or personal data. As the findings show, the participants might not be fully aware of if and how their data is being gathered, and do not know if they have given informed consent before they are handing over their data. If the students are not informed, they might feel pressured to participate in LA services without knowing the conditions, risks, and benefits. Institutions should direct their focus on informing students thoroughly and asking for informed consent before or during the data collection. This should give the students the option to regulate or drop involvement at any point if they do not want to share information. Thus, this can be challenging since it can cause only partial data analysis with limited analytical power, giving inaccurate results. In other words, students can benefit from better analysis by sharing larger amounts of data.

This addresses cost-benefit scenario that participants mention in the analysis. This displays the willingness for participants to participate in a trade-off where they sacrifice something and get something else in return. The students' concern related to privacy decreased if the data was used specifically to improve their learning or learning environment. In other words, if the data was collected and analyzed and presented to them giving them useful information to either personalize their experience or give them intuitive features that LA could provide data collected would be understandable. West. et al. (2020) found similar results that indicated a need for benefits to outweigh concerns.

According to Madden (2014) users of online services often share data in exchange for services or discounts. If students were more actively engaged and informed of both its advantages as well as the data practices implemented to protect and use. They might share more data willingly and be better protected when doing so. Thus, this can result in students having to take active decisions about privacy and ethical that are important. However, it might not align with students' intent when they log on to these systems and therefore feel like a distraction or obligation that could be perceived as a burden. Which can explain that research shows that students are unlikely to read Terms and Conditions agreements (Khalil et al., 2018; Prinsloo & Slade, 2015). Hence, as noted in the analysis chapter the students care about "Quality of Information" and are sensitive to being flooded with information when they engage in the LMS, and this could cause them to avoid the system all together. This implies that students should be given access and active choices to consent, but with some emphasis in avoiding information overload. Prinsloo and Slade (2016) suggest nudges could subtle way of doing this. According to the authors the nudges avoid being too complex and informative enough for students to understand what the possible benefits of accepting the specific consent.

This approach can be compared to the consent form users are met with when they enter new websites and need to accept different cookie and data sharing options. Furthermore, this approach could be aligned with GDPR Recital 30 that mentions cookies and Recital 32 that states "Consent should be given by a clear affirmative act establishing a freely given, specific, informed and unambiguous indication of the data subject's agreement to the processing of personal data […] This could include checking a box when visiting an internet website,“ (The European Parliament and the Council 2016, p. 13). This also means that withdrawal is an important factor, where students can actively choose if they want to participate in LA functions or not. In the study from Norway Presthus and Sørum (2021) found that GDPR has not significantly affected their belief in level of control over their own personal data, nor affected their awareness about storage and use of personal data. This indicates that nudging students to act towards consent during engagement in digital learning environments is rather complex and could end up not functioning as intended. Thus, giving students access and control over their own personal data can increase trust and decrease the vulnerability of both them and institutions, and with this control they might be more willing to share data.

For institutions to tackle students' unease about privacy and ethical issues, they need to provide transparency, awareness, and openness about how and why they collect, store, and use student data. According to Selwyn (2019) this can involve redesigning LA with emphasis on "socially sympathetic" design approaches that values different social contexts in which LA is likely to be used, as well as addressing diverse needs and rights of users, and most important makes sure that users are informed about their involvement and engagement. Further, Selwyn (2019, p. 16) describes it as "user-respectful" design (as distinct from "user-friendly" or "user-centred"), which foregrounds issues relating to privacy, security, and user rights.".

When mentioning informed involvement, it refers to awareness and consent to LA engagement as mentioned earlier. Institutions should give students the right to consent and give straight forward information about their rights when it comes to their personal data. Lastly there needs to be certain rules for who can access the data, such as authorized personnel to protect appropriate security measure. This brings us to another challenge that LA poses for students in higher education. The students mention that they are worried that teachers can gain too much access to their data and analysis. However, they mostly agree that the data can be beneficial for teachers and instructors in personalizing teaching and giving faster and improved individual feedback. Yet, they fail to mention or ask about the ownership of the data, and who owns the data analysis generated by LA. If this is not addressed it can cause potential trust issues and misuse of student data, as analyzed material might change, shifting ownership away from students.

This implies that institutions should make sure to have clear policies and guidelines when it comes to the use of LA. One possible way could be by actively engaging students in the decision-making process and find out how students prefer to tackle privacy and ethical issues they come across in digital learning environments. Another way could be in ensuring that both institutional staff and students are trained in privacy and ethical dilemmas. Participants privacy and ethical concerns might not come as a surprise it stresses the absence of students' active involvement when it comes to development of LA in education. As noted in previous research Slade and Prinsloo (2013) notes that an ethical principle should emphasis involvement of students voices when developing LA tools for education.

Lastly the theme "Determined by Numbers", LA can also cause ethical concerns when it comes to the use of algorithms and predictive modeling of students. As noted in the analysis the students are concerned that for example personalized analysis be beneficial, but also the risk of inaccurate can cause negative consequences on individuals. Such predictions are often gathering data on myriad of data set provided by big data and can include a so called "background check" that includes demographic data etc. this can result in algorithms in being biased against certain groups of students, for example students from disadvantaged backgrounds. Noble (2018) comments that data-driven decision-making systems can work as (dis)advantageous for different social groups that are less represented in systems dataset. Meaning that certain design of algorithms objectives can reproduce existing social inequalities or discrimination and generate new ones through data-driven analytics. In relation to this thesis could see that this point to broader concerns that LA services and features can impact some groups of students or teachers more than others.

Moreover, if there is uneven distribution of data in a dataset or lack of data it could provide incomplete or inaccurate data for LA models leading to biased or incorrect decisions towards students. Avoiding this outcome and addressing the students' concerns one needs to make sure that analysis of data does not happen in a black box, where unexplainable things and conclusions are made. Institutions need to make sure that the analysis like predictive model algorithms are explainable and transparent. To ensure that LA are accurate and precise they need to be regularly evaluated to see if they hold any unwanted bias or discrimination.

6.3 How do students believe LA will impact their education?

When it comes to the participants' perspectives on how LA will impact their education and learning they are mostly positive, but they still have concerns. This means that they have a belief that LA can be beneficial during their studies. From the theme "Usage of LA" we find that participants believe that LA can help them identify areas where they might need additional support, information, or resources and give personalized instructions. Thus, students have different experiences and expectations and needs to be adjusted to fit personal preferences. Which can cause a dilemma of "LA, help or hindrance to learning?". This might be because some students have personal preferences when it comes to learning and education. E.g., some prefer a lot of assistance and guidance during learning, while others like to follow a strict template with traditional approach or textbooks. As noted earlier the participants believe that LA can help teachers and instructors improve personalized learning in their education and are willing to sacrifice personal data if they are being provided with beneficial personalized instructions. The data can provide instructors with valuable insight and information in each student's learning needs, styles and preferences. This is done by analyzing the data so instructors can identify needs and give targeted support to help them succeed (Leitner et al., 2017).

However, these beliefs of "Usage of LA" are mostly rooted in ideals about how things could be if LA would be implemented the right way. But as noted by some of the participants they believe it is technologically possible to implement LA in their education, they still issue forth how this can be done in practice. One way of interpreting this would be to say that they have high ideal expectations, but when it comes to real expectations, they are lower, since they are having trouble seeing how their data could be useful for data analysis since they do not use digital learning environments enough to provide useful and insightful information for any analysis to take place. When it comes to “Usage of LA” students interact with the four LA objectives and techniques presented in 2.3 Data Analysis Techniques and Objectives that can impact “LA being helpful or a hindrance for learning”.

As noted earlier, in LA tools students often interact with descriptive and diagnostic analytics thought LADs. The participants point out that LA can help in observing and understanding their own learning preferences and styles. When it comes to LA to observe personal learning, they tend to prefer summaries of LA analysis that resemble dashboards interfaces. Some of the participants point out that they like the idea of LA dashboards but are not sure if they would use it. Rets et al. (2021) points out several beneficial features of LADs. Furthermore, LADs can help students in self-regulating their learning, and have impact on motivation, grades and remembering tasks and other obligations (Rets et al., 2021). However, when evaluating LADs research, Jivet et al. (2018) discovered that pedagogical approaches and theories are frequently overlooked in the design and use of these tools. Additionally, uncovered only weak evidence for positive learning outcome from LADs and that not all learners perceive all aspect of LADs as positive. Such findings can underline the importance of LA having strong fundaments in learning theory (Siemens & Long, 2011) and personalized LA development that is tailored for individual needs (Viberg et al., 2022).

Predictive and prescriptive analysis can help identify what kind of support may be needed for students and give personalized feedback or recommendations. Participants believe that LA it could help with personalized feedback and assistance for their learning with for example recommending and personalizing tasks and curriculum. Additionally, believing that such analysis can assist and help at-risk students giving them guidance or reminders to achieve intended learning goals and catch up with the rest of the class. A way of giving such feedback is by notifications or feedback in a learning environment. In a research project conducted by Lawrence et al. (2019) they explored the effectiveness of using course-specific LA to encourage students to participate more actively in their courses. The study showed that students who received explicit guidance and support, along with early nudges, were able to prioritize key course-specific resources and achieve better outcomes. The study demonstrates that specific feedback provided by LA can help encourage students to get involved at an early stage and improve their overall experience in courses in LMS. Thus, participants are concerned that such recommendations could become to frequent and not be specific enough. Further challenges pointed out is if feedback is not accurate, causing confusion and leading to demotivation or students getting misleading feedback. Selwyn (2019) points out that this could in a self-fulfilling prophecy causing students to believe inaccurate feedback.

Despite there being potential advantages, Greller and Drachsler (2012) also points out some drawbacks with one concern when identifying at risk students with predictive LA that it can go both ways. The student may alter its study behavior with increased effort in studies or it can result in a negative behavior in students self-fulfilling the prediction. Thus, the act of making predictions is a common practice in the field of education, where students assess their own progress and teachers have the competence to observe and make predictions about their students. The point being that LA have the capability of using the combination of detailed data for parametric in the analytics when profiling students impact student self-efficacy both positive and negative (Greller & Drachsler, 2012). However, making accurate predictions from students activity and academic data can be challenging. Gašević et al. (2016) states that it can be challenging to make comprehensive conclusions based upon LA research since the studies are often contextualized in specific learning environments. Which makes it difficult to both compare and draw transferable solutions from one context to another.
Banihashem et al. (2018) highlight some data-related challenges such as the difficulty of data collection, standardization, and ensuring data quality. Greller and Drachsler (2012) suggested a solution for this problem, emphasizing that one could make generic LA framework that could support replication, comparison, and alternating contexts. Making LA easier to implement and make it easier for agents such as teachers and administration to analyze, interpret and report on the data. However, as noted in 1.3 Previous Research, Gašević et al. (2016) criticized this notion by stressing the implications of generalizing LA models, as it can threaten LA in being adapted to the context specific learning environment. This also challenges findings in this study, where participants are not homogenous and have different expectations of how LA should and could work for them. Another possible solution could therefore be found by standardizing the way data LA is stored (Kunnskapsdepartementet, 2022a), In Norway there has the later years been put in effort to standardize data gathered and used for LA. This contributes to making use of data gathered in a regional context and additionally, giving institutions the possibility to both compare and analyze regional data in comparison with their own and adapting frameworks to suit their needs.

Something else pointed out by some of the participants is that LA could be used as control management by teachers in detecting who are not visiting the LMS and penalizing or helping students who are not contributing to group assignments or doing their online assignments. Authors like Bodily et al. (2018); Ferguson (2012) and more emphasizes that early identification of student performance issues can help prevent academic failure, which matches results a study done by Foster and Siddle (2020) where they found that students are more likely participate when provided with notifications reminding them to engage in course content. So indeed, having LA to early prediction and notification of both teachers and learners could be an effective way of avoiding students to fall behind. Thus, the participants also point out that they dislike this form of control management. Despite this being a normal thing to expect in a physical classroom.

Moreover, there is also a concern that data might be interpreted by teachers causing bias or personal opinions about the students that they do not want to share with the teacher or institution. Further, the participants worry that such analysis could turn them into numbers and remove the human part of education where they are being formally determined by analysis and data as numbers in a system. These viewpoints can be compared to a sociotechnical perspective in emerging concerns of implementation of LA in education. Selwyn (2019) article has contributed to a more critical view of LA implementation. Here he mentions two arguments for the need to be critical. Firstly, as LA has become a key element of contemporary education it is important these services and technologies that LA offers shape the education and academic lives and outcomes of future students. Secondly, he mentions that it is important to challenge the idea that LA can be treated as a neutral tool that is flexible and can be used in any way. In other words that LA can be used " for good or bad, wisely or carelessly, effectively or ineffectively." (Selwyn, 2019, p. 12). Thus, this point of view can be comforting and bears a common-sense logic, it does overlook the sociotechnical nature of the impact of technology on us humans. The sociotechnical perspective states that technologies have an influence on people's behavior. At the same time technology is not just a product of design, development, implementation, and usage, but also shaped by external factors such as social, cultural, and political aspects. In other words, the sociotechnical perspective emphasis that LA is interconnected with complex structures of the society that contribute to further development, adoption, implementation, and functionality.

LA can function as and provide a source of motivation for students (Ferguson, 2012) It can also assist students in observing, organizing workload, creating personalized feedback and learning paths during their studies(Leitner et al., 2017). All this can give new tools for the students that can possibly impact efficiency, learning outcome, engagement, and motivation. However, some participants state that this can impact the individual learning process. One participant points out that recommendations could cause learners to miss the broad picture or other possible solutions. Meaning that learning might become simplified by LA, removing important part of the process that students might lose when having analysis doing it for them. One participant describes this as the ‘knowledge process’ that learners are confronted with when engaging in learning activities. A consequence of wide implementation and use of LA tools in educational setting could cause LA to simplify learning rather than supporting it and make students become dependable on LA technology when obtaining new knowledge in the future. The reflections made by the students resembles Wajcman (2019) term “new behaviorism”, implying that individuals can be nudged and steered into behavior management, influencing peoples decision-making and actions. In other words, monkey see, monkey do.

Despite the possible benefits of LA, there are also some general concerns on how LA can impact education at present. As mentioned above they rooted in the accuracy and validity of the personal data that is collected on them. As the participants have different learning styles, they are worried that they might not produce the right kind of data to satisfy data analysis. Making LA produce wrong assumptions about them as students. Furthermore, the participants seem to have concerns about LA becoming a tool for surveillance as they are being observed during engagement in digital learning environment and are obligated perform and produce data to satisfy data analysis. This can impact their autonomy and privacy when engaging in such systems. An interesting argument made by Selwyn (2019) is that users can have different agency when using digital environments based on their conscious awareness of statistical awareness. Meaning that users that are aware of that how their activity data can impact data-driven decisions in LA by satisfying those parameters to achieve better outcomes, while others with lack of awareness will fall short when using the digital system without being mindful of statistical value their activity data might have. In short, this raises concerns about unequal data-driven decision-making that LA systems are likely to encounter from students. An example would be that one student was aware that ‘time spent on task’ was a deciding factor in grading on that task, and the student would adjust time spent just to impact the grade. As a result, the student altered the behavior to satisfy the algorithms, rather than maybe having a more natural approach.

With the example above in mind, one can ask who LA benefits in this context. In an underlying sense one could interpret that this is primarily benefiting the needs of the institutions. Where students are altering their behavior to satisfy data-driven decision-making rather than focusing on their learning needs and styles. With this perspective it could be argued that 'end users' or the main stakeholder are not students. Meaning that LA services primarily could end up being products that satisfy the interests of institutions and other third parties that benefit from specific outcome from users. An example could be a learning app that has core interest in making profit from end-users' activity, they could use LA to make it more entertaining, rather than more focus on knowledge acquirement for users. As mentioned by numerous researchers it is important LA is concerned about learning (Ferguson, 2012; Gašević et al., 2015), and that the main stakeholders should be (Viberg et al., 2022; Whitelock-Wainwright et al., 2019). Selwyn (2019) takes it one step further, reflecting on that the main end-users of LA are increasingly machine-based and not even human. He makes this assumption based on that data is being transported between systems, recirculated, altered and processed by other algorithms, and systems. Thus, as of now this might be a challenge of the future of LA in higher education.

7 Conclusion and further research

In this study we explored first-year pharmacy students' expectations of LA in their education and how they believe learning might be affected. It is essential to explore the expectations of students as they are the main stakeholders of LA. This is to ensure that LA is implemented to meet students' expectations and needs in system to be functional for the students and be accepted by them. The research results are based on students' experience with digital learning environments and limited awareness of LA. Nonetheless, the participants have different concerns related to ethical and privacy implications of data gathering and LA implementation that should be considered when developing and implementing LA technology. The students believe LA can provide additional support, information, or resources and facilitate personalized learning and education. Thus, students have different experiences and expectations and LA needs to be adjusted to fit these personal preferences. This emphasizes the importance of making students aware of any LA initiatives planned or occurring within the institution. Although it is a challenging task to create policies and systems that solve the differentiation in viewpoints of students, it is crucial to involve them in the decision-making process. Higher education institutions should establish guidelines and protocols for obtaining student consent when collecting and using their data to maintain students' trust and personal privacy preferences. Institutions must respect European GDPR law, respecting individual rights to control their personal data and preferably following international instructions developed by Jisc (Sclater & Bailey, 2015).

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APPENDIX 1

Introduksjon (Uten lydopptak)	○ Takk for deltakelse! Dine tilbakemeldinger fra erfaring og mening er verdsatt! ○ Gi grunnleggende informasjon om prosjektet, masteroppgaven, hensikten med intervjuene og om min rolle i prosjektet. ○ Dette er et semi-strukturert intervju og vil kunne minne om en dialog mellom oss to. ○ Intervjuet blir opptatt på lyd og sikkert lagret. ○ Dine uttalelser i intervjuet vil kun bli brukt i forskningssammenheng og anonymisert, slik at uttalelser ikke kan føres tilbake til enkeltpersoner. Vi vil be deltagerne om å undertegne en konfidensialitets-erklæring, slik at erfaringer og tanker som deles i intervjuet ikke formidles videre til utenforstående. ○ Målet er at samtalen mellom oss ikke skal vare lengre enn 1 time og du kan når som helst trekke deg fra prosjektet og all informasjon du har gitt oss kan bli slettet. ○ Har du noen spørsmål før vi begynner?	**Huskeliste** - Samtykke skjema - diktafon/lydopptak - Notatblokk - Avtal tidspunkt og lokasjon
Tema 1 Bakgrunn	1. Fortell om deg selv 😊 2. Hvorfor valgte du farmasi utdannelsen? 3. Lever utdannelsen opp til forventninger så langt? -faglig, sosial og **digitalt** 1. Hvordan vurderer du din evne til å planlegg og evaluere egen læring? 2. Hvordan syns du selv din interesse til studiet reflekterer din prestasjon? 4. Hvordan bruker du teknologi og digitale verktøy i utdannelsen? b. for å finne ekstra kunnskap? c. for å komme i kontakt med medstudenter? d. for å løse oppgave? 5. Hvordan bruker du Mitt UIB?	**Skru på lydopptaker** 4. the background of the students digital literacy LMS helpful or a burden
Tema 2 **Innhold og design**	1. Hvordan tror du innhold og design påvirker deg når du bruker nettsider og apper? (hva kjennetegner dem?)	Stikkord til sp4: tilpasset opplæring med tanke på læringsstil.

	2. Du har kanskje vært på ** å få reklame som er perfekt for deg Hvordan tror du store selskap som FB, YT og Google tilpasser innhold og reklame til deg? 3. Når man åpner en nettside, også skal man godta cookies/informasjonskapsler? 4. Tror du det kunne vært nyttig å gjøre noe lignende i din utdanning?	Multimodal design quiz = tilbyr mer innhold på de deler av quiz som man presterer dårlig på.
Tema 3 Digital lærings-analyse	3. Mitt UiB kan observere studenters digitale spor og generer mye aktivitetsdata, hva tenker du om det? - Var du klar over dette? – mer åpent 4. Tror du data kan beskrive deg som person? – mer åpent - how can data describe you as a person 5. Hvorfor er viktig for deg hvem som har tilgang til din data? 6. Kunne du tenkt deg å ha tilgang til din data? 7. Tror du informasjonskapsler/cookies kan hjelpe deg i studiehverdagen?	
Måter å bruke LA på	1. Hvordan ville du reagert om du fikk «diagnostisert» din prestasjon og læring? - for eksempel at man utforsker din data og sammenheng for å beskrive din prestasjon og læringsstil som student? 2. Om du hadde en analyse fra data om deg, hvordan skulle den vært presentert til deg? Når og hvordan? Hvor mange detaljer? Dashboard? 3. Kunne du tenkt deg dette som en obligatorisk del av utdannelsen? - Hva hvis det var bevist at det øker ditt læringsutbytte? (Og SP) 4. Hvem sitt ansvar syns du det burde være å vurdere og behandle aktivitetsdata samlet fra Mitt UiB? - Kunstig intelligens? Analytikere? 5. Kan du tenke deg til noen fordeler og ulemper med analyse og bruk av slik data? 6. (Forklar Deskriptiv og diagnose analyse) Hvilke muligheter tror du en slik analyse kan ha for deg? 7. (Forklar Prediktiv og anbefalings analyse) Hvilke muligheter tror du en slik analyse kan ha for deg?	Kjernepunkt: dataene kan gi innsikt som grunnlag for blant annet tilpasset opp-læring

	8. Helhetlig, hvordan tror du analyse av din aktivitetsdata kan påvirke din motivasjon under utdanningen?	
Tema 4 Avslutning	1. Er det noe mer du føler du ikke fikk sagt under intervjuet? 2. Hvordan syns du det var å svare på spørsmålene mine?	**Til slutt** - Takk for intervju - Skru av lydopptaker

APPENDIX 2

FREMFARM: Å utdanne farmasøyter til å møte morgendagens utfordringer

Samtykkeerklæring

Jeg har mottatt og forstått informasjon om:

- Prosjektbeskrivelse av FREMFARM: Å utdanne farmasøyter til å møte morgendagens utfordringer.
- Innhold i intervjuet og lengde.
- har hatt anledning til å stille spørsmål.

Jeg er enig i:

Ved å delta i fokusgruppe- eller intervju godtar jeg å delta i studien.

Jeg godtar at opplysningene mine vil bli behandlet til prosjektet er fullført.

Dato: ________________________________

Navn: ________________________________