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Thesis Social Comparison in Educational Interfaces: Leaderboards and Progress Indicators

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Abstract

Student-facing learning analytics dashboards have led to providing actionable feedback to the students through visualizations like charts and progress indicators. Some of these visualizations allow students to compare themselves with their peers. The impact of such comparitive visualizations has been researched in the past few decades and most of the works have produced conflicting evidence. Leaderboards, or comparitive charts have been utilized to motivate students. These create competition that can influence the students positively or negatively. The influence of learning interfaces that combine leaderboards and progress indicators has not been thoroughly explored. This study aims to describe the behavior of students on an online learning dashboard featuring multiple social comparison elements, specifically progress indicators, and leaderboards.

We designed a dashboard, containing progress indicators and leaderboards, that was used by the students in a university course. Interactions with the dashboard were tracked throughout the course and were used to showcase differences in behavior between the students. Interpersonal differences among the students were captured through validated questionnaires, and clusters of students were further explored to analyze the patterns of their usage and engagement with the system. We also examined the students who used the system more seriously and classified them as learners. We found that clusters based on personality differences did show significantly different interactions on the dashboard. These differences were the most noticeable in their interactions with the leaderboard. However, no significant differences could be found between the learners who actively performed interactions that indicated self-reflection compared to those who didn't. Pre-knowledge of the student also didn't seem to be an important factor in determining the engagement and interactions of the students. We infer that the tendency to compare with the peers, as well as goal orientation are among the important factors that decide students' engagement with progress indicators and leaderboards. This study highlights the need for future research on the influence of individual differences on online learning dashboards that contain multiple social comparison elements.

Keywords: Learning Analystics, Dashboard, Progress Indicators, Leaderboard, Social Comparison

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Chapter 1

Introduction

Technological advancements in the past decades have made their way into education through multiple systems and tools supporting interactive, online learning and assessment [24, 20]. As the popularity of online learning grew, students' interaction with the platforms led to a lot of unused but useful data. By integrating learning analytics (LA) into online learning, this data can be used to further enhance learning for students [40, 10, 44]. LA refers to the measurement, collection, analysis, and reporting of data about learners and their contexts [13]. Such data, in this context, can consist of performance on assignments, grades, or learning progress. This information is visually represented on a dashboard, using graphs and diagrams, which are more engaging and easier to comprehend than text [35, 29, 4, 28]. For students, such dashboards improve tracking learning progress and making decisions about future learning steps. Numerous different types of dashboards could be added to aid a learning management system, differentiating in which elements of the course are visually displayed. For example, a dashboard focused on social interactions would prominently feature statistics about students' communication, while a more performance-oriented dashboard would feature statistics on grades or how many assignments have been submitted.

The addition of an online learning dashboard unfortunately does not fix all the flaws of online learning. Communication in an online course becomes more limited and less personalized compared to a traditional course [37]. In a traditional course, students could walk up to their teachers to receive immediate feedback. This feedback is easily accessible and can be adapted instantly if additional comments are made during the student-teacher interaction. Giving feedback online is more difficult and might not be as personalized as in the traditional course. This is even more of an issue in large-scale courses. Furthermore, online learning is less engaging and motivating to students than classroom learning [17, 42]. A traditional learning environment provides its students with the motivation to keep up with its learning materials [36]. Motivation is gained by, for example, interacting with fellow students. Online learning is less structured than traditional teaching, which emphasizes the need for motivating aspects of dashboards, so it encourages students to not fall behind on learning. Learning online is more based on the students' agency to study, which further highlights the need for extra motivation in online learning.

Teacher-facing dashboards can aid online teachers in providing personalized and comprehensive feedback, a teacher can easily see which areas particular students are struggling with and tailor their feedback with those areas in mind. Student-facing dashboards, on the other hand, could even guide students to assignments that were analyzed to be helpful for the students. However, this feature does not fully address the lack of motivation and engagement of students in online courses [17, 42].

In the context of increasing motivation in online learning, the concept of social comparison has been explored a lot [45, 34]. To evoke comparisons on an online learning dashboard, social comparison elements need to be introduced on the dashboard. Social comparison stems from Festinger's social comparison theory [11], which states that people have an innate feeling to compare themselves to others to evaluate themselves. This comparison provides the comparer with an evaluation of their skill. Social comparison can result in a positive and/or negative influence on motivation and engagement. The resulting influence varies between people and could be determined by differences in personality and perspective on the comparison. To introduce social comparison in online learning dashboards, the dashboard needs to include social comparison elements. A frequently used element is the progress indicator [32]. These display information regarding the user's progression on tasks. These indicators can be used to induce social comparison from its users by showing the average progression on tasks for the entire class next to the student's progress on the same tasks. Another element, that can introduce social comparison, is a leaderboard. A leader-

board shows a list of names and scores, sorted from highest score to lowest. A leaderboard has already been shown to increase engagement and motivation in students [2, 47]. However, several studies have found that in some situations, leaderboards can be seen as overly-pervasive and can induce destructive competition [19], and inadvertently harm engagement [7]. To benefit from a leaderboard as a social comparison element, there is more research necessary on how to effectively use it to gain profitable outcomes, like an increase in motivation and engagement.

In this thesis, we explore the differences in behavior of students based on their differences on a social comparison-led interface in an online learning support system. We introduce a combination of progress indicators and leaderboards in an online learning system. This project involves the development of a dashboard based on leaderboards and topic-level progress indicators in the *StudyLens* Knowledge Map. *StudyLens* is a recently developed Learning Support System (LSS) that is currently being piloted in several UU courses. The leaderboards with progress indicators will be a dashboard component in *Studylens*. The proposed visualizations will be validated in the context of an undergraduate university course. During the course, the interactions between the components and students will be tracked. Afterward, a survey and interview will be taken to get the preferences of the students regarding both social comparison elements. This data will be used to answer the following research objective: How do students interact with a dashboard containing a leaderboard and other social comparison elements?

The thesis starts with a thorough literature review (Chapter 2), explaining the theoretical aspects related to learning analytics and social comparison. Then we discuss the detailed research plan and methodology (Chapter 3). In the next chapter, a system description is given, which explains the implemented system and its design choices (Chapter 4). In addition, it also covers the course's setup, which will be used for the data analysis. Chapter 5 contains the results and Chapter 6 discusses these results with previous work and its limitations. The thesis ends with a conclusion on the research (Chapter 7).

Chapter 2

Literature review

This study investigates interactions on a dashboard containing a leaderboard and other social comparison elements. Though there have been numerous studies on the effects of such elements, most research has resulted in mixed conclusions. Since learning supporting systems are already a popular topic and frequently used in an educational setting, finding ways to improve them could increase the educational value students earn from them. This review starts by discussing recent works on learning analytics and dashboards, followed by an explanation of other topics like social comparison, leaderboards, and progress indicators.

2.1. Learning Analytics

Learning analytics (LA) refers to 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. [13] In many LA-driven systems, all bits of educational information are gathered and progressed by a dashboard about learners to improve learning and teaching. This can be used in multiple levels of the educational system: for example, teachers would be able to track which exercises the students find difficult, while students could get more support from a dashboard that tracks their completion numbers and lacking areas. The educational information consists of a variety of data, such as engagement, attendance, and grades. There is a lot of potential for improving e-learning with the correct use of LA. Therefore, there has been a lot of research regarding this using different types of learning dashboards.

Schwendimann, et al (2017) [38] conducted a systematic literature review of fifty-five learning dashboards to create a checklist for future learning dashboard implementations. Even though the area of learning dashboards is considered young, a lot of different visualizations of dashboards are considered usable. There are no unique visualizations for the educational setting: all visualizations used were from other fields. Most of their conclusions showed that this is a new field and needs more research, specifically in comparing different dashboards with other dashboards.

Several studies have focussed on student-facing dashboards. A student-facing LA dashboard is a user interface specifically for students to manage their activities and progress. Teasley (2017) [43] investigated the flaws of a one-size-fits-all approach for a student-facing dashboard. These dashboards give an unclear representation of the student's performance, which results in the students having to connect the representation with their actions. It also includes visualizations of the student's performance in comparison to their classmates. This one-size-fits-all method is supported by a single algorithm for the assessment of performance and feedback, which means the students' assessments are not based on their performance and that all students receive very similar evaluations of these aspects. By incorporating social comparison theory into a student-facing dashboard, the dashboard could motivate underperforming students by navigating them to relevant material to improve instead of constantly being shown an upwards comparison of the other students.

Despite the lack of unique visualizations in an educational setting, Sedrakyan, et al (2019) [39] design principles for dashboard designers to choose their visualizations of the data. They recommended different methods for choosing visualizations based on design concepts found in previous research and visualization paradigms. Visualizations were judged on subjective perceptions, scalability, and the perspectives of students and teachers. There is no conclusive best visualization because it all depends on multiple factors: context, data characteristics, objectives, reasons for visualizations, and relevance.

Thesis

Since there is no best visualization, we could use many different forms of visualization in learning dashboards. Kokoç and Altun (2021) [25] used five different learning dashboards with distinct goals and visualizations to see to what extent the interaction data can be used to predict and provide guidance to students in academic performance. Their five dashboards were designed as follows:

- Their basic usage dashboard included bar charts showing the total time spent or the total amount of clicks.
- Their learning objects dashboard included interactions with activities. The tracked data is similar to the basic usage dashboard since it includes the total time spent on activities and amount of clicks.
- Their discussion activities dashboard showed the interactions with the forum, including how many forum posts were created and amount of clicks.
- Their assessment dashboard showed their exam scores and averages of exams in line graphs.
- Their recommendations dashboard gave the students risk charts and personalized recommendations based on their interaction data and predicted end grades of the course.

They found that participants who interacted more with any dashboards had higher academic achievement. Furthermore, the strongest predictor of higher academic achievement was interactions with the recommendations dashboard. The writers argued that this was because of the use of risk graphs and the provision of supportive suggestions.

2.2. Social comparison

The utilization of social comparison can improve a LA dashboard by providing more personalized feedback and can thus better stimulate motivation. Festinger's social comparison theory [11] states that people have an innate feeling to compare themselves to others to evaluate themselves. There are two different directions towards which someone could socially compare themselves: either upwards or downwards. Upwards comparison happens when someone compares themselves with someone they view as better, while downwards comparison happens when someone compares themselves with someone they view as worse. The effects of both social comparisons can vary between people and this variation is caused by the comparer's perspective on the comparison. Upwards social comparison could have a positive influence on the comparer, evoking positive affect, or making the comparer feel worried. Similarly for downward social comparison, it could evoke both negative and positive effects [27, 6]. There are also two other types of social comparison: lateral and temporal social comparison. Lateral social comparison refers to comparing yourself to others who seem to be similar to the comparer on various traits. Temporal social comparison involves comparing yourself to a future or past version of yourself. These two types are here for completion, but the following researches mostly use only upward and downward comparisons.

Comparing ourselves to each other in education has been observed in students at a very young age. Dijkstra, et al (2008) [6] gathered literature regarding the social comparison habits of children in elementary school and found that children have different ways of social comparison from adults. Most relevant in regards to leaderboards, children prefer to perform upwards comparisons. The target of the comparison is usually someone who performed better or who resembled themselves on related or unrelated attributes. These attributes would make their comparisons more informative since it would increase their self-efficacy. Preferring upward comparison suggests that students unconsciously strive for self-improvement. Several works have addressed the intricacies of the effects of social comparison and have shown how the direction of comparison may have both positive and negative effects. A classic study by Medvec, et al (1995) [30] researched counterfactual

thinking in people and analyzed the reaction of athletes in the 1992 Summer Olympics. They found that the silver medalist winner turns their potential positive upward comparison into a negative upward comparison when comparing with the winner of the gold medal. On the other side, the bronze medalist turns their positive downward comparison into a negative one by looking down on all the other competitors who did not receive medals. Figure 2.1 summarizes the contrasting effects of comparison made by athletes competing for medals [15].

	Upward Comparison	Downward Comparison
Positive Effects	Hope, Inspiration	Gratitude
Negative Effects	Dissatisfaction, Envy	Scorn

Figure 2.1: Contrasting effects of Upwards and Downwards Comparison [15].

Since social comparison already happens naturally at an early age, it could be used to manipulate positive feelings later in life as well. Fleur, et al (2023) [12] investigated whether social comparison could increase motivation, metacognition, and academic achievement on a learning analytics dashboard used in higher education courses. They performed two experiments with different dashboards. Both dashboards contained a graph that displayed your performance and the performance of students with similar goal grades, with a hidden preference for students performing better to encourage upwards social comparison. The difference lies in the presence of a probability distribution graph of the student's estimated final grade. The removal of this graph eliminated the possibility that the prediction might have influenced the tested variables rather than social comparison. In both experiments, the treatment group performed better academically and had higher extrinsic motivation at the end of the experiment. They concluded that their carefully designed dashboards increased the motivation and performance of students using social comparison.

In the previous works, upwards comparison was preferred (and sometimes the only comparison that could be made) by the researchers to be performed by the students. Allowing students control over their social comparisons could influence them to only make comparisons they want to make. This could increase the chances of only beneficial social comparisons. In a study done by Akhuseyinoglu, et al (2022) [2], they implemented a learner-controlled leaderboard in which students could choose which range of scores could be visible in their leaderboard. It yielded positive results concerning the engagement of the system and the intensity of their practices. The preferences for either downwards or upwards were explained using learners' differences: higher social comparison orientation favored upwards, while performance-oriented and performance-avoidance favored downward comparison.

2.3. Leaderboard

Leaderboards are a popular device used to show social comparison information. A typical leaderboard (Figure 2.2) is based on a score and ranks the scores from highest to lowest, highlighting the top rankings. Each row in a leaderboard typically shows a name and its corresponding score. They are typically used in games or sports. Several (other) gamification elements have also been introduced in a learning environment to create a positive influence. Gamification uses mechanics from games to engage and motivate people to reach goals in non-game contexts. It features elements



(d) World of Warcraft, video game

Figure 2.2: Leaderboards come in all shapes and sizes, but all have a few things in common. These four leaderboards are all sorted based on an aspect that is visible on their respective leaderboards. Sometimes multiple aspects are taken into account when sorting the leaderboard, as shown in (Figure 2.2c). Some leaderboards even display additional information that does not influence the sorting of the leaderboard, like the amount of chess games won and lost and even more statistics (Figure 2.2a) or the different builds and skills the character used to get their score (Figure 2.2d). Leaderboards often feature other gamification elements as well, like the use of badges or personalization items in the leaderboard from *Duolingo* (Figure 2.2b).

from games like achievements, levels, or leaderboards to incorporate into this non-game setting. The design of these elements cannot be copied exactly from games and needs to be designed with an educational context in mind. When incorporating it into a learning system, it would not be optimal to use the same design. A lot of designs have been implemented and tested. Below are a few important examples of these designs and their principles.

Park and Kim (2021) [33] gives three design principles when designing leaderboards:

- Leaderboards should both be designed on macro and micro levels.
- Integrate each measurable element with a micro leaderboard.
- Leaderboards should incorporate activities other than learning activities.

Leaderboards should also create constructive competition between students. This can be achieved when the competition is fun and supports growing positive interpersonal relationships. However, leaderboards are often destructive competition, because the progress of other students is easily viewable, allowing for more social comparison and usually highlighting one winner at the top [19]. Some principles, discovered by Featherstone (2018) [9], to increase the constructive competition that is relevant to our leaderboards are:

- Non-prescriptive measurement means that tasks can be split into sub-tasks.
- Cohort-based play. This allows the users to focus on working together to clear a goal, instead of working against each other to individually clear goals.
- Multiple measures of progress: allow users to gain scores by doing multiple activities.
- Asynchronous play. The leaderboard and system can be viewed outside of the classrooms.
- Virtual rewards.
- Avatars.
- Elective participation. The user is not forced to participate in every activity and activities are split up into shorter events.
- Player matching.

The influence of gamification and gamification elements has been a popular research topic and has therefore been researched frequently. Fotaris, et al (2016) [14] investigated the difference in attendance, performance, and motivation of two courses, with one of the courses using three different games instead of traditional lectures. They incorporated a quizzing website with a leaderboard (*Kahoot*) and a game based on the show *Who Wants To Be A Millionaire*, which is a trivia game with increasing difficulty, to be used during the lectures. The practical exercises were done on *CodeAcademy*, which has (weekly) challenges for the students to complete. They observed that the attendance of the course with gamification elements was higher than the traditional course. They also were more motivated to study the additional learning material throughout the week, with higher download rates than the traditional course's students. The practical exercises had an increasingly higher completion rate throughout the course for the gamification course, which could be due to the motivation of the weekly challenges. In the end, the gamification course also had a better overall academic performance.

Another research by Huang and Hew (2015) [21] that again investigated a traditionally given course and a gamified course observed the positive influence of their gamification elements. The gamification elements they added were badges, points, levels, and a leaderboard. Both courses were

set up with post and pre-course activities available on the course's website. Students who were a part of the gamified course engaged more with the site and posted more on the course forum. The gamified course also participated more in the post-course activities. However, this could have been due to the gamified course having a reward when completing post-course activities, while the traditional course did not. There were no significant differences in academic performance between both courses.

However, research has also suggested some negative effects whenever a leaderboard has been used in an educational setting. Hanus and Fox (2015) [19] compared two curriculums: one with a leaderboard containing badges and one without these gamification elements. The students of the course with gamification elements showed less motivation, satisfaction, and empowerment. They concluded that future research should focus on the effectiveness of specific gamification elements rather than the whole concept.

Domínguez, et al (2013) [7] created a leaderboard based on the amount of gained achievements to support an already established e-learning platform. The gamification elements were created only for the exercise part of the course. Students could gain achievements and badges by performing and completing exercise tasks. The leaderboard showed both of these. They also added social comparison by including a comparison view in which students could compare their achievements with other students. The percentage of users having a specific achievement was also visible. One of the major issues that they found was the lack of immediate feedback for the performed exercises. The exercises were immediately seen as correct whenever they got submitted as a way to replicate the immediate feedback in games. This allowed students to be able to cheat to get achievements and higher standings on the leaderboard. Their findings were mixed since students who participated in the gamified exercises performed better overall and on practical assignments, but worse on written exercises. These students also participated in fewer in-class activities. They conclude with the importance of the design phase of any gamified element, to be able to achieve a beneficial effect for the students.

One crucial benefit from any gamification element in an educational context is increasing the intrinsic motivation of the students, but a study by Mekler, et al (2013) [31] using an image tagging platform did not observe any increase in intrinsic motivation for their three tested gamification elements (leaderboard, points, and levels). Their players had to tag images based on a shortly visible image. Introducing the gamification elements did increase the throughput of the system, which still makes these elements a nice way to boost user performance for simple tasks. They do reason that the throughput is probably higher because these elements would allow players to set explicit goals for themselves. These goals could be formed by seeing how many images the number one ranked player had done, for example.

The influence of positions on the leaderboard on engagement and competition has been investigated by Bai, et al (2021) [3] using two different leaderboards. One leaderboard showed their absolute positions, while the other only showed a relative position. They concluded that most students were positive towards the use of leaderboards for social comparison and competition. The students performed more social comparisons with the absolute leaderboard, and their sense of competitiveness was increased compared to the relative leaderboard. Students in the lower bottom third rankings had different opinions regarding the anonymity of both leaderboards. For the absolute leaderboard, they preferred it to be anonymous, while in the relative leaderboard, there was a preference for a public leaderboard.

2.4. Progress Indicators

Progress indicators are tools used to visualize and track the progress of students. They can be used to identify areas in which the students struggle and their overall progress in the course. They are

implemented in a variety of shapes and forms depending on the contexts in which they are used. For example, a progress indicator for a math course would probably include the accuracy of their solutions, while a progress indicator for a language course would probably include how many (new) words have been learned. The visualizations used for the indicator can also be in many different forms, like a grade, charts, or feedback on submission. Progress indicators allow users to view their progress over time, help them, and identify their weaknesses.

Wyatt (1994) [46] conducted a literature review on education indicators, which is one of the many words with the same meaning as progress indicators. In the 1980s, progress indicators were proposed as a solution for the diminishing budgets for resources for education systems. They also could provide a means of monitoring change, which would fit with the diminishing responsibility of schools. Progress indicators have been referred to different terms, thus leading to different definitions described in their review. The most frequently used definition was the one by Burstein, et al (1989) [5], which stated the progress indicators should provide at least one of the following types of information:

- Information that describes the education system's performance in achieving desired educational conditions and outcomes;
- Information about features known through research to be linked with desired outcomes;
- Information that describes central features of the system in order to understand how a system works;
- Information that is problem-oriented;
- Information that is policy-relevant.

Furthermore, progress indicators should have the following technical characteristics:

- Indicators should measure ubiquitous features of schooling that can be found in some form throughout the system;
- Indicators should measure enduring features of the system so that trends over time can be analyzed;
- Indicators should be readily understood by a broad audience;
- Indicators should be feasible in terms of time, cost, and expertise required for data collection;
- Indicators should be generally accepted as valid and reliable statistics.

Some progress indicators in educational settings indicate the completion rate of the activities in a course. In some cases, they represent students' knowledge level based on formative assessments that are taken during the learning process to evaluate the students' understanding of the taught subject. Some implementations provide a more fine-grained indication of the progress with respect to students' progress or knowledge across various topics and subtopics of the course. Mastery Grids [26] (Figure 2.3) combines the ideas of an open learning model with social visualization to boost the engagement of students with progress indicators. Open learning models have been shown to motivate and navigate students to appropriate content. It shows the student's progress and gaps in their knowledge. Social visualization approaches are based on social comparison theory. Mastery grids are a three-dimensional visualization component defined in a domain and navigable resources. The cell shows the intensity of color, which denotes the level of mastery. They performed an evaluation based on students from three courses. They found that performing educational actions, which was based on eight different actions students could perform, was associated



with a higher grade. The subjective responses about the usability and usefulness of mastery grids were positive.

Figure 2.3: This image showcases one of the visualizations of mastery grids used in the research by Loboda, et al [26]. The upper half of the image allows the user to see their mastery compared to the group. The researchers added a timeline underneath it for visibility on the topic of the week. The bottom half shows the individual learners in the group and their grids.

Recent works demonstrate the potential of learning systems that use several of the ideas mentioned above. However, few works study interactions of these elements, which leaves a research gap in the understanding of what leads to an effective leaderboard and progress indicator system.

Chapter 3

Methodology

As briefly mentioned in the introduction, the research objective of this study was as follows:

How do students interact with a dashboard containing a leaderboard and other social comparison elements?

This is explored further using the following research questions:

- 1. Do the individual differences impact learners' interaction with the dashboard that compares their progress with their peers?
- 2. Do the learners interacting meaningfully with the dashboard achieve more in terms of interactions than their counterparts?
- 3. Does the dashboard support low pre-knowledge students, and does this eventually impact their future performance?

This section describes the design and methods used to answer the research question further.

3.1. Study design

This research was organized as an observational study. It was conducted during the Evolution-2 course (Course code: B-B2EVO09), which is an undergraduate University of Utrecht Biology course. The course was only available for students who completed the previous course (Evolution-1) two years ago and builds upon the knowledge gained in the previous course. 189 students had enrolled in the course. It consisted of 7 lectures and three formative tests with a midterm and endterm test. The tests were structured with one before the first lecture and the other two split evenly during the lectures. The first test served as an initial knowledge check, to see how much knowledge the students had retained from the previous year. The other two tests tested the knowledge gained from the lectures. Lectures were given every week and the complete schedule is visible in Appendix A. Accompanying each lecture was a practicum, which gave the students questions that they needed to solve with the information learned in the lecture.

This project falls under a larger project "Personalized support of student motivation based on learning analytics" which is funded by the Utrecht Education Incentive Fund (USO) and has been approved by the Ethical Review Board in 2022. This project went through Utrecht University's Ethical and Privacy QuickScan since it involves human participants. The full document is added in the Appendix B. It was allowed to proceed.

3.2. Research instruments

The dashboard was filled with learning material that the teacher and teaching assistants had provided for us. These were given before the course had started and the students could access them whenever their corresponding lecture was given. The system and these materials are explained further in the next section (Chapter 4).

Before participating in this research, the students were asked to fill in a consent form (Appendix C). After agreeing to the consent form, the participants were asked to fill in our pre-questionnaire (visible in Appendix D), which gave us insight into their personality, goal orientation, and social comparison habits. The pre-questionnaire included questions taken from the following surveys:

- Achievement Goal Questionnaire [8]; this deduces the students' achievement goal orientation, which can be a performance-approach, performance-avoidant, mastery-approach, or mastery-avoidant orientation.
- Iowa-Netherlands Comparison Orientation Measure (INCOM) [16]; INCOM is used to measure the participants' social comparison habits, like how often someone compares themselves and on which aspects.
- Big 5 10-item personality inventory (TIPI) [18]; TIPI is used to measure the personality traits of the participant on different characteristics: extraversion, agreeableness, conscientiousness, emotional stability, and openness to experience.

To collect the data to analyze students' interaction with the dashboard, we processed the application logs to compute measurements that describe their engagement and progress. System logs were present in an Actor-Verb-Object format with the corresponding timestamp. In this format, the Actor was an anonymized *userid*, verb were interactions like *loading*, *answering*, *closing*, etc. Objects represented components of the dashboard or the learning material, each with an identifier associated with them. We computed a lot of variables using the system logs:

- The students' quiz scores and specific topic scores to display on the leaderboards.
- The students' amount of clicks on each feature of the dashboard, like the learning material, leaderboard, and practicums.
- The amount of time the students spend on each of the main features of the dashboard.
- We tracked how many times values were changed or revisited, like how many times the star rating was changed on an answer or which learning material was revisited the most.
- Using both time and clicks we computed meaningful interactions with the learning material. It was defined as the next interaction needed to be longer than a minute after the opening of a learning material.
- The logs allowed us to also gather week-by-week data of the students.

Participants were also asked to fill in a post-questionnaire (visible in Appendix E) when the course had finished. This post-questionnaire included questions regarding their attitude towards the system and whether they were willing to participate in future interviews. Students mentioned the randomly assigned identification number, the *userid* that was provided to them. We did not receive any personally identifiable information from any of the students.

3.3. Approach

To answer the research objective, these research questions described above investigate the patterns of interactions and the influence of individual differences on the interactions. They defined multiple patterns of interactions that together could incorporate the most helpful interactions students could perform. To answer these questions, we did:

- 1. We looked at the personality and pre-knowledge of learners. Firstly, We divided the students based on personality clusters, which were made using hierarchical clustering. We also created a threshold for which students could be defined as learners (to remove students who did not use the dashboard in a meaningful way). Afterward, we checked for each cluster of learners how they behaved on the dashboard and their pre-knowledge scores. An analysis of the different interactions, using one-way ANOVA and Tukey's range test, resulted in individual differences in interactions.
- 2. Next, we split the learners even more on their meaningful interactions by also splitting them on a non-mandatory but helpful interaction on the dashboard (namely, rating their practicum answers with stars). This analysis used one-way ANOVA and Tukey's range test again.
- 3. For the last sub-question, we needed to define low pre-knowledge students. We then looked at their improved or worsened quiz scores. Secondly, we checked the interaction differences between the groups of low pre-knowledge students and analyzed them using one-way ANOVA and Tukey's range test.

We proposed the following hypothesis for the sub-questions:

 H_1 : Learners show a difference in interactions based on their personality clusters and the combination of pre-knowledge and their personality clusters.

This sub-question aimed to see if there already is a difference in behavior based on personality alone. We expect that if the clustering is done correctly, students with different personalities should interact differently on the dashboard. For example, students with lower INCOM scores should not interact with the social comparison elements as often as students with higher INCOM scores. Furthermore, pre-knowledge could have influenced their behavior on the dashboard. Combining both individual features incorporated all the individual features that we tracked throughout this research.

 H_2 : Learners performing meaningful actions achieved more on the dashboard than learners performing not as many meaningful actions.

This question aims to differentiate the interactions that the dashboard can have. Students are allowed to interact with the dashboard however they want. This can cause some unintended behavior like students just pressing the completed button while not having completed the learning material. This way they can boost, and therefore cheat, the learning progress, making their placement and comparison with the rest of the class wrong. We expect that learners who did behave meaningfully achieved more than learners who did not.

 H_3 : Low-performing students who interacted more with the dashboard managed to improve their quiz scores more than low-performing students who did not interact as much with the interface.

The interface is supposed to guide and navigate students to new and helpful learning material. This guidance is especially helpful to low-performing students. These students need all the support from the dashboard to improve their grades and understand the material. If this hypothesis is true, then we could argue that the use of the dashboard helps low-performing students improve and that the dashboard provides guidance and navigation to students.

Chapter 4

System description

The new interface has been created in *StudyLens* [1], a learning support system, aiming to help students visualize their progress and access learning materials. *StudyLens* has been used in various courses offered by the Department of Information and Computer Sciences and the Department of Biology at the University of Utrecht. It is usually offered as a supplementary tool for the students to work on additional problems, track their progress, and view remedial material to fill their knowledge gaps.

The primary interface of the system is called a Knowledge Map that shows visualizations representing the topics of a course, students' progress on them, and links to learning material associated with them. The system offers formative assessments in the form of quizzes. In the quizzes, each question is a multiple-choice question with the correct answer connected to one of the topics or constructs related to the course. The score is computed by aggregating the scores through a treelike hierarchy of topics and subtopics. *StudyLens* has been described in Sosnovsky, et al (2020) [41] and Joshi (2022) [22]. This system has been created using React (frontend), Python (backend), and MySQL (database), and has been hosted on Utrecht University servers.

In this research, we designed a new interface for *StudyLens*. Previously, the Knowledge Map showed the lectures in chronological order with different activities and topics shown in a tree structure. The tree structure allowed the students to see how activities and topics were related to each other. Each node in the tree structure also contained double bars to show your progress compared to the classes. Additional functionality was added to support the learning material and practicums provided by the teachers.

STUDYLENS						evo2201
nowledge map ivolution-2						
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± 5////////////////////////////////////	137.	1	evo2201	5.0	0%	
Feb.5	138.		evo2148	5.0	0%	
	139.	1	evo2054	5.0	0%	
	140.		evo2113	5.0	0%	
	141.	1	evo2175	4.0	<mark>9.0</mark> 9%	
Variatio 8 mutatio	142.	- Store	evo2189	4.0	<mark>9.0</mark> 9%	
	143.	<u>🔶</u>	evo2062	4.0	<mark>9.0</mark> 9%	
алан бу 	144.	1	evo2083	4.0	<mark>9.0</mark> 9%	
Feb.14 LEARNING MATERIAL	145.	2	evo2067	4.0	<mark>9.0</mark> 9%	
	146.	1	evo2008	4.0	<mark>9.0</mark> 9%	
	147.	1	evo2163	4.0	0%	
	148.	2	evo2188	4.0	0%	
Patronen van Evolutie	149.	2	evo2159	4.0	0%	

Figure 4.1: The interface of the course dashboard on Studylens.

In Figure 4.1, the new interface created for this study is visible. While designing the new interface, we followed the existing system style guidelines to make the new interface look consistent with the existing components of the system. The left side of the page shows the lectures with practicums

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vertically in chronological order. Each lecture contains a practicum button, and a title and shows your progress and the average progress in two bars. Clicking the practicum button will take the user to a screen shown in Figure 4.4. The user can solve the questions and score their answers based on five stars. Back to the lecture node, the first bar showcases your grade for the lecture with the filled-in blue bar and the progress in the lecture with the blue and white striped bar. Underneath the bars are the learning materials, which are related materials to this specific lecture.

This system offers the following types of learning activities:

- Reading material, represented by a book icon. This activity contains chapters from a specific book the students have to read.
- Videos, represented by a camera icon. This activity contains a video (and a link if the video is not loading) that the students have to watch to complete the activity.
- Articles, represented by a newspaper icon. This activity embeds an external article or a webpage in the component.
- Factsheets, represented by a page article. They are short summaries, glossaries, or cheat sheets prepared by the teachers of this course.
- Interactive activities, represented by a mouse icon. This activity has an interactive module, which the students have to interact with to complete this activity.

When clicking on an activity block, the activity will be shown in a pop-up with a button to mark the activity as *Completed*. When a student completes an activity, a checkmark is shown on top of the icon for that activity. An example of an activity pop-up is shown in Figure 4.2.

						evo2201 [→
Knowledge map Evolution-2	Mark as complete	Biology 121 section 123 The ac	Haptive landscape principle	ŧ	а х е :	
Quiz 1 Results Ceografie var 4 5 Feb. 5 Practiciant		Biology 121 section 123 The adaptive landscape principle Magnetic section of the section of the section of the section adaptive landscape model is useful way of combining could adaptive landscape model is useful way of combining could of the coccepts, with illustration. Imagine appellation which, over evolviously time, has above on a graphic libration - reading principle way and above on a graphic libration - reading that is a real population but we can picture the principle with a couple of vanishes, like	Mo, was the first researcher to suggest the dify to the idea of adaptive landscapes. The non-probability process, and environmental net is instanded to provide a bitcl coverview environment of the second second second second the average values of its genes disquesticities, and adaptive the second second second second the second second second second second second second second second second second second the second second second second second second second second second second second second second second second second second seco		Í	che drift Fylogenie 3
Feb.14 Prectourn Prectourn Patronen V	If the link above is not loading or showing pl https://www.coolling.ubc.col~bes/16/217.51	n the second sec	evo2159	4.0	0%	

Figure 4.2: An activity pop-up screen on Studylens.

In addition to the learning activities, we also implemented a component for long-form questions that is made available with each topic. These questions were accessed by pressing the practicum button. Students could fill in and self-grade their answers with the star rating feature. A week after the practicum was released, the correct answers for each question were shown underneath the answer box.

The course was divided into seven topics. There were three formative tests, or quizzes that were made accessible at the beginning of the course, around the midterm, and at the end of the course. The top-left section shows links to attempt or review the quizzes (Figure 4.3). The right side of the interface shows the leaderboard with the user highlighted and on the top of the leaderboard. For each student, the leaderboard shows students' rank, their avatar, anonymized username, score, and progress. By default, the leaderboard shows scores and ranking based on the last attempted quiz.

The filters on the top of the leaderboard allow the user to view the leaderboard for the chosen topic. On clicking one of these filters, the leaderboard refreshes to show students' ranking, score, and progress for the selected topic. Meanwhile, if a filter is selected, the topic tiles on the left high-light the related learning materials with a brighter color, thus nudging them to navigate to the topic-related activities. Users' progress and ranking changes as they interact more with the learning materials. Figure 4.1 shows the activities filtered on the topic "Fitness": some activities are grey-colored, while others are blue. This will allow students to navigate to specific topic-related activities quickly to increase their scores. A specific topic-based leaderboard is also shown, which means in this example that only the score and learning progress of "Fitness" are shown on the leaderboard.

Formative Test 1	¢	×
Questions 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24		
Chapter 22, Descent with modification: a Darwinian view of life Which of the following statements about Lamarck tot scurete?		
A. Lamarck thought evolution had occurred.		
B. Lamarck proposed a mechanism for evolution.		
X C. Lamarck thought organisms became more complex because of an inner drive for complexity.		
D. Lamarck published his ideas only after Darwin published his.		
Concepts		
Fitness		

Figure 4.3: A review quiz pop-up screen on Studylens.

Mark as complete Chapter 4: Mutation and Variation 0								
Autations are a relatively rare phenomenon, and individual mutations often have rather small effects. For these reasons, measuring mutational effects on fitness and other phenotypic traits is a challenge. For more than 40 years, evolutionary biologists have used mutation accumulation (MA) studies to determine the effect of spontaneous mutations on some phenotypic character. In these MA experiments, mutations are allowed to accumulate in lines that are maintained for several to hundreds of generations. The large number of generations permits the researcher to detect relatively small effects. In these experiments, a small number of ndividuals (or sometimes a single individual) are randomly selected each generation to continue the line; this process ensures that the effects of natural selection are minimized, allowing mutation and random genetic affit to be the main evolutionary processes that alter the genetic composition of the lines.								
The nematode worm Caenorhobditis elegons has several features that make it well suited for MA studies. Its small size and large number of progeny per individual make this worm easy to study in laboratory experiments in general. Because it has a short generation time (noughly 3 days), many generations can be produced in a fairly short period of time. These nematodes also can be frozen for storage and revived later; this permits one to measure anxectors and distart descendents at the same time and under the same set of conditions.								
A team of researchers then at the University of Oregon investigated behavioral changes of worms that occur as mutations accumulate. Michael Lynch has been performing MA studies in a variety of organisms to examine mutational components of fitness and phenotypic traits. Patrick Phillips and his postdoctoral fellow Susanne Estes have been investigating the evolutionary genetics and chemosensory behavior of C elegans.								
Beverly Ajie, at the time an undergraduate at the University of Oregon, examined the responses of worms from the MA lines to chemical stimuli, as part of her honors' thesis.								
In the MA experiment, a single, randomly-selected individual was permitted to start the next generation. One of the advantages of using C. elegans for mutation accumulation studies is that these worms are hermaphrodites, capable of fertilizing themselves.								
The MA experiment started with 100 replicate lines; of these, 67 survived by the time of the behavioral study 370 generations later.								
Question 4.1 What potential bias does this loss of lines introduce?								
Write your answer here								
It's quite possible that some of the lines were lost because they had accumulated so many deleterious mutations they couldn't propagate themselves. Because those lines would have had more severe mutational effects than average, their loss could lead researchers to underestimate the true extent of deleterious effects due to mutation accumulation.								

Figure 4.4: A practicum pop-up screen on Studylens.

The decision to create multiple leaderboards is supported by the research done by Park and Kim (2021) [33]. Our leaderboards follow their relevant design principles: that leaderboards should be designed on a macro and micro level and that each measurable element needs to be integrated into a micro leaderboard. Their third principle is not relevant to our system, since there were no activities other than learning activities. Our macro leaderboard is the total leaderboard, which incorporates each topic. Each topic and its scores and progress are described in a micro-level leaderboard. Activities related to the topic are highlighted whenever the user visits a micro-level leaderboard, which provides easy navigation to relevant activities.

Furthermore, to create constructive competition in our system, we used the principles from Featherstone (2018) [9]. The non-prescriptive measurement denotes that tasks can be split up into subtasks, to reward the completion of sub-tasks. In our system, each task is a lecture or a topic, which is split up into multiple learning activities for which the user is rewarded for completing these activities. Users are also able to skip activities if they get stuck, but are not rewarded if they do not complete the activity. Another principle describes asynchronous play, which is true for our system because it will always be available during the time of the course.

Chapter 5

Results

The goal of this research is to examine the students' interactions with the dashboard and determine the influence of individual differences on these interactions. This section answers the subquestions and the research question on how the students interact with the dashboard. It starts with the descriptive statistics of the pre-questionnaire. From the pre-questionnaire, we defined clusters using hierarchical clustering in the first and second sections. This section ends with the summaries of the three interviews conducted after the course ended.

5.1. Pre-questionnaire & Clustering

A pre-questionnaire was taken during the first session with the dashboard. It contained questions from three different established questionnaires: the Achievement Goal Questionnaire [8], the lowa-Netherlands Comparison Orientation Measure [16], and the Big 5 10-item personality inventory [18]. It was filled in by 70 participants (a response rate of 37.04%). One set of answers had to be disregarded due to not providing answers for each question. The following section goes through each of the included questionnaires in order and describes each of their descriptive statistics. Furthermore, this section also covers the clustering progress made using hierarchical clustering in the last subsection.

5.1.1. Achievement Goal Questionnaire

The Achievement Goal Questionnaire [8] questions gave us insight into the students' achievement goal orientation. The questionnaire consists of 12 questions with a 7-point Likert scale. Each three questions represents a different achievement goal. It was filled in by 69 participants. The complete overview of the questionnaire is shown in Table 5.1. The subscale score of mastery-approach and performance-avoidance is high, considering that each subscale could have a maximum score of 21 and a minimum score of 3.

	Subsca	le scores	Questions		
	Mean STD		Mean	STD	Cronbach's alpha
Performance-approach goals	10.40	4.33	3.41	1.64	0.88
Mastery-avoidance goals	10.80	3.90	3.51	1.58	0.79
Mastery-approach goals	14.84	3.07	4.91	1.24	0.81
Performance-avoidance goals	13.34	3.74	4.33	1.70	0.73

Table 5.1: The summary statistics of the Achievement Goal Questionnaire.

5.1.2. Iowa-Netherlands Comparison Orientation Measure

The lowa-Netherlands Comparison Orientation Measure (INCOM) [16] differentiates between two different ways of social comparison, namely comparisons based on ability or opinion. It consists of 6 questions with a 5-point Likert scale. The INCOM questions were answered by 69 participants, but 2 students were disregarded due to not filling in this particular section. From the summary statistics (Table 5.2), it can be noticed that the students performed more opinion-based comparisons since the opinion subscale's mean is higher than the ability subscale's mean. Furthermore, the opinion subscale's mean is high considering that the maximum score would have been 15 and a minimum score of 3.

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	Subsca	le scores	Questions			
	Mean	STD	TD Mean STD Cro		Cronbach's alpha	
Ability	8.72	2.78	8.77	2.69	0.72	
Opinion	11.06	1.79	10.79	1.91	0.60	

Table 5.2: The summary statistics of the Iowa-Netherlands Comparison Orientation Measure.

5.1.3. Big 5 10-item personality inventory

The Big 5 10-item personality inventory [18] measures the students' personalities on five scales. Each question had a 5-point Likert scale with a score of 1 being 'Strongly Disagree' and a score of 5 being 'Strongly Agree'. 69 participants provided answers to this questionnaire. As visible in Table 5.3, results in each of the scales varied a bit. Most noticeably, most participants were more agreeable and less emotionally stable than average.

	Subsca	le scores		estions	
	Mean	STD	Mean	STD	Cronbach's alpha
Extraversion	2.40	1.02	2.45	1.27	0.48
Agreeableness	3.37	0.64	3.33	1.03	0.16
Conscientiousness	2.91	0.84	2.86	1.29	0.38
Emotional stability	2.15	1.08	2.14	1.36	0.45
Openness to experience	3.32	0.97	3.27	1.28	0.35

Table 5.3: The summary statistics of the Big 5 10-item personality inventory.

5.1.4. Clustering

To aggregate students' responses to the Achievement Goal Questionnaire and the lowa-Netherlands Comparison Orientation Measure Questionnaire, we conducted hierarchical clustering to group them based on their goals and social comparison traits. The Big 5 10-item personality inventory was excluded from clustering because their internal consistency (Cronbach's alpha values) was too low to be reliable. After thorough experimentation with the Ward method [23], we found the clusters to be most meaningful when we had four clusters. We studied their scores on each sub-scale to assign a label to each cluster. It resulted in four clusters: Uptight, Moderate, Non-comparing, and Confident cluster. As visible in Figure 5.1, these clusters varied a lot in their subscale scores over the six metrics.

- The Uptight cluster (n = 12) has the highest performance and mastery-avoidance scores. Having a high performance-approach and -avoidance score means that these students want to perform well and better than their peers. Their high mastery-avoidance gives the cluster the concern whether or not they can completely master this subject and not fall behind their peers. Furthermore, they also score higher than the others on the ability scale. This emphasizes the importance for them to compare themselves against their peers. Lastly, they also score quite high on Mastery-approach, which supports that they want to learn and master this subject.
- The Moderate cluster (n = 30) has average scores across the scales, except for masteryavoidance. Their average scores are all very close to the means when looking at all the students (shown in Table 5.1 and 5.2).
- The Non-comparing cluster (n = 12) has very low scores on the lowa-Netherlands Comparison Orientation Measure. These students do not care about comparing themselves against their peers. This is supported by their lower avoidance scores.



Figure 5.1: Each of the clusters' subscale scores in all the subscale scores used in the clustering: their achievement goal orientations and social comparison habits.

• The Confident cluster (n = 11) has similar scores as the Uptight cluster, however these two differ on the avoidance scales. This makes the Confident cluster less interested in comparing with their peers and less concerned about not being able to learn the subject. They can therefore seem more confident in their abilities. They are almost equally enthusiastic to learn and master the course as the Uptight cluster.

To emphasize the clusters' differences on these subscales, we used one-way analysis of variance (ANOVA) to determine whether there are significant differences between the means of all the clusters' subscales. If ANOVA results in a significant difference, a Tukey's range test is done afterward. This is a post-hoc test used to compare all possible pairs of means. The result of the Tukey's range test gives insight into which groups' means are statistically significantly different. Performing ANOVA on mastery-avoidance resulted in significantly different means (F(3) = 3.618 & p = 0.018). A Tukey's range test showed that the Uptight and Moderate clusters were significantly different (p = 0.009). Similarly, performing ANOVA on ability showed significantly different means (F(3) = 15.268 & p < 0.001). Tukey's range test found that the Uptight cluster was significantly different against the Non-comparing (p < 0.001) and Confident clusters (p = 0.003). Furthermore, the Moderate and Non-comparing clusters were significantly different (p < 0.001). Lastly, the Moderate and Confident clusters were almost significantly different in ability (p = 0.060).

The students in different clusters also show different behaviors on the dashboard. Firstly, their behavior on the leaderboard was significantly different between some of them. Their total leaderboard interactions are visible in Figure 5.2. After performing one-way ANOVA on the leaderboard interactions for each cluster, it resulted in the groups having significantly different means (F(3) = 3.582 & p = 0.018). Performing a Tukey's range test, the groups that different are the Uptight and Non-comparing clusters (p = 0.016). Furthermore, Uptight and Moderate were almost significantly different (p = 0.083). Secondly, the Non-comparing cluster stopped using the leaderboard (one of the social comparison elements) after the fourth week of the course. This behavior was not visible for any other cluster.



Figure 5.2: The leaderboard interactions for each of the clusters throughout the course.

Some clusters also had different pre-knowledge scores. Performing one-way ANOVA on the data shown in Figure 5.3 resulted in almost significant differences (F(3) = 2.688 & p = 0.055). However, performing a Tukey's range test did show significant differences between the Uptight and Non-comparing clusters (p = 0.016). This test also resulted in an almost significant difference in pre-knowledge between the Uptight and Moderate clusters (p = 0.059).



Figure 5.3: The pre-knowledge (quiz 1) scores for each of the clusters.

Lastly, the clusters also showed different personalities in the Big 5 10-item personality inventory. As shown in Figure 5.4, the emotional stability subscale varied a lot between the clusters. Performing one-way ANOVA on the emotional stability subscale scores resulted in significantly different means between the groups (F(3) = 3.608 & p = 0.018). The Tukey's range test showed that the Uptight and Confident clusters are significantly different in emotional stability (p = 0.013).



Big 5 10-item personality inventory subscale scores for the clusters

Figure 5.4: The clusters' subscale scores for Big 5 10-item personality inventory.

To summarize, four clusters were made based on the Achievement Goal Questionnaire [8] and lowa-Netherlands Comparison Orientation Measure [16]. Using the subscales of these questionnaires we described their personalities:

- The Uptight cluster, who like to compare themselves and learn and master the subject.
- The Moderate cluster, who were average on almost all the subscales.
- The Non-comparing cluster, who did not like to compare themselves.
- The Confident cluster, who, similarly to the Uptight cluster, like to learn and master the subject, however, they compare themselves less.

The personality clusters made using hierarchical clustering behaved differently on the dashboard. Furthermore, the clusters also showed significant differences in their pre-knowledge grades and emotional stability scores.

5.2. Usage of the system

This section introduces the learners of the course. We define the differences in learners on their personality clusters and interactions. Subsequently, we analyze if the individual differences resulted in different interaction behaviors on the dashboard. Another individual difference we analyzed was the pre-knowledge differences in learners. Afterward, we took a closer look at low pre-knowledge students and their interactions. To conclude this section, we introduce *super-learners* and analyze their knowledge gain compared to learners.

5.2.1. Identifying learners

The dashboard contained a lot of different ways of interaction: a leaderboard, multiple quizzes, multiple practicums, and all the learning material. We observed that not all interactions are valid or helpful interactions to the students. For example, opening and closing a learning material within 5 seconds cannot be recognized as a valid interaction with the learning material. A student cannot absorb the knowledge of the learning material within this short period. Furthermore, since the dashboard contained a lot of progress bars that showed the percentage of completion, it was possible for students to gamify the system [7] in this way. We therefore decided to only focus on students who performed a lot of *good interactions*. The *good interactions* were classified as a learning material interaction in which they spend at least a minute in the learning material. We only filtered on this specific type of interaction, since this was the only interaction that could boost your percentage in the progress bars. This filtering left us with 63 learners of which 32 filled in the prequestionnaire and could be sorted into clusters: 7 Uptight, 15 Moderate, 6 Non-comparing, and 4 Confident learners. With this subset of students, we aim to answer the first subquestion: whether individual differences influenced the learners' behavior on the dashboard.

5.2.2. Learners' quiz scores

The course contained three non-mandatory quizzes that students could willingly take after they had been released. Almost all learners completed the three quizzes, as shown in Table 5.4. Looking at the learners' clusters' scores (Figure 5.5), there is quite a difference in pre-knowledge scores. After performing one-way ANOVA, there are significantly different means between the clusters (F(3) = 3.037 & p = 0.046). Tukey's range test shows that this significantly different mean is between the Uptight and Moderate clusters (p = 0.050). The Uptight and Non-comparing clusters have almost significantly different means (p = 0.067). For the other two quizzes, one-way ANOVA showed that there was no significant difference between the clusters (F(3) = 0.549 & p = 0.653, F(3) = 1.029 & p = 0.395).

	Ν	mean	STD
Quiz 1	30	6.18	1.28
Quiz 2	32	6.19	1.32
Quiz 3	30	6.05	1.25

Table 5.4: The amount of learners that completed that quiz, mean and standard deviation of each of the quizzes.



Figure 5.5: Each of the learners clusters' quiz scores. The learners who did not finish a quiz are removed from the graphs.

5.2.3. Learners' interactions

Other than the quizzes, the learners also enthusiastically interacted with other parts of the dashboard. Since learners are defined by their meaningful interactions with learning material, we began with their learning material interactions. We counted the number of unique learning material the learners performed meaningful interactions on. There were a total of 64 learning materials in the Evolution-2 course. As shown in Figure 5.6, there is a lot of variance in this metric between the clusters. Performing one-way ANOVA between them resulted in no significant difference between them (F(3) = 2.011 & p = 0.135).





Figure 5.6: Each of the learners clusters' amount of unique learning material that they have performed a meaningful interaction on.

Another interaction we were interested in was the amount of leaderboard interactions since some clusters already had significantly different means when using the clusters with all the students. As shown in Figure 5.7, it looks like there could be significant differences between the clusters. Doing a one-way ANOVA analysis revealed that there are significant differences between the groups (F(3) = 4.804 & p = 0.008). Performing Tukey's range test showed that the Uptight and Moderate clusters have significantly different means (p = 0.025). Similarly, Uptight and Non-comparing have significantly different means (p = 0.007).



The leaderboard interactions the learners made, split on cluster

Figure 5.7: Each of the learners clusters' leaderboard interactions.

Lastly, the dashboard contained an optional rating interaction for students' practicum answers. This did not affect the dashboard in any way but only represented a way for the students to indicate self-assessment of their long-form answers to the questions. Students had the option to rate their own answers using stars. The average rating of non-zero ratings (only counting filled-in ratings) was 2.90. Not every cluster interacted much with the stars, as shown in Figure 5.8, but there are some outliers that did interact with them in every cluster. Similarly to the unique meaningful interactions, no cluster had significantly different means after performing one-way ANOVA (F(3) = 0.502 & p = 0.684).





Figure 5.8: Each of the learners clusters' star interactions.

5.2.4. Does pre-knowledge determine interactions?

We also analyzed whether the pre-knowledge score of the learners determined students' interaction with the dashboard. We expected learners who scored lower on the pre-knowledge quiz to interact more with the dashboard to fill their knowledge gap. On the other side, it is not expected that learners with a high grade for quiz 1 would interact way more with the dashboard. Their personality clusters also could influence this expected behavior. As previously shown in Figure 5.5, their pre-knowledge scores varied a bit. To determine whether pre-knowledge scores influenced their interactions, we performed simple regression on their scores and a specific interaction type. This resulted in mostly very weak (r < 0.20) positive relations between the scores and interactions. However, when testing learners with more than 20 practicum answers (N = 52) on the influence of pre-knowledge on the answer interaction a weak positive relation was found (r = 0.21 & p = 0.138). As shown in Figure 5.9, a small positive relation can be seen between the features.



Figure 5.9: Regression performed on learners with more than 20 answer interactions. Regression was between quiz 1 scores and answer interactions of the learners.

Since the learners-only regression did not give any interesting insights, we performed regression on all the students who finished quiz 1 (N = 180). This also resulted in mostly very weak positive relation between the pre-knowledge and the tested interaction. However, there was once again one weak positive relation between pre-knowledge and the leaderboard interaction (r = 0.22 & p = 0.033) (shown in Figure 5.10). This regression analysis was done with all students who performed at least five leaderboard interactions and finished quiz 1 (N = 109).





Figure 5.10: Regression performed on all students with more than 5 leaderboard interactions and a finished quiz 1. Regression was between quiz 1 scores and leaderboard interactions.

To summarize, personality did seem to influence the learners' behavior on the dashboard. Individual differences regarding pre-knowledge did not give us enough evidence to conclude that they

influenced the learners' behavior. The relation between pre-knowledge and specific interactions behaved in the opposite way that we expected. For that reason, we can accept H_1 for the personality differences. However, we cannot accept H_1 on pre-knowledge differences.

5.2.5. Low pre-knowledge students

Since pre-knowledge did not seem to influence interactions, we then analyzed whether the dashboard effectively supported low pre-knowledge students. This can be determined by analyzing the interaction behavior of the students whose performance improved over time and the ones whose didn't. Low-performing students were classified based on their pre-knowledge quiz (the first quiz) scores. Students who scored below a passing grade (< 5.5), were classified as a low pre-knowledge student (N = 81). To check for improvement, we split the low-performing students into students who did improve their grades for either of the following quizzes, scored the same, or students who performed worse. To see if the dashboard could be credited for their improvement and therefore accept H_3 , we analyze whether there are significant differences in dashboard interaction between these groups.

An interaction can be defined in different ways. Firstly, we only looked at the amount of clicks a user had. Using one-way ANOVA, no amount of clicks on any interaction type yielded any significantly different means between the improvement groups. Secondly, we only looked at the time spent in part of the dashboard. For example, how long the students were observing a learning material (by looking at the 'open' and 'close' interaction time). For this analysis, the low-performing students were divided based on whether they achieved a high, average, or low grade for either quiz 2 or 3. The boundaries for a high, average, or low grade were made based on the grade distribution from their respective quiz. This analysis was done using one-way ANOVA between these three groups of low-performing students, for each time spent aspect we tracked. Similarly, to the clicks, almost no significant difference was found between these groups except for one aspect. The low-performing students were split based on improvement on quiz 3, which resulted in 44 students who got a grade below 5.97, 6 students who received a grade higher than 7.1, and 17 students who got a grade in between the previous values. Performing one-way ANOVA on time spent in practicums resulted in almost significantly different means between the three groups (F(2) = 3.041 & p = 0.055). However, performing Tukey's range test afterward did not yield any significant difference between the means of the groups. This is visible in Figure 5.11.





Figure 5.11: Low scoring pre-knowledge quiz students were split up based on their scores for quiz 3 in either high, average or low scores. The boxplots display the amount of time spend (in minutes) on practicums for each student in each group.

From these findings, we could argue that the dashboard did not help the low-performing students improve their scores. Therefore we cannot accept H_3 .

5.2.6. Combining self-reflection interactions with learners

When filtering out the learners initially, we only looked at their meaningful learning material interactions. The dashboard contained one more good identifiable interaction, that could filter out even better learners. The star interaction allows students to self-reflect on their answers and helps them in their learning progress. This interaction does not influence their learning progress percentage and can therefore not be gamified. This was a completely optional feature of the dashboard, that could easily have been ignored by the students. However, the learners did interact with it (as shown in Figure 5.8), making it possible to identify some *super-learners*.

To identify the *super-learners*, we took students who had the most interactions with stars and meaningful interactions with the learning material. From both of these groups, we only took the top 25%. The *super-learners* are the students that are in both of these groups. In the end, we identified 17 *super-learners*. These 17 *super-learners* are also learners and 9 of them have personality clusters, namely: 2 Uptight, 4 Moderate, 2 Non-comparing, and 1 Confident.

We want to compare their improvement against different groups. These groups are the top 25% of both stars and meaningful interactions, the middle groups of both stars and meaningful interactions, and the lower groups of both of these interactions. Since the *super-learners* are the intersection of both the 25% groups, we also included the union of the 25% groups in this analysis.

To check if the *super-learners* improved differently compared to the other groups, we calculated all of their knowledge gains based on this formula:

$$knowledge_gain = ((z(Q3) + z(Q2))/2) - z(Q1)$$
(5.1)

The z(x) stands for the z-score of a specific student for a specific quiz. A z-score stands for how many standard deviations the value is from the mean. Since the first quiz was about the previous course, the score for the first quiz determined the students' pre-knowledge. The second and third quizzes were about their respective halves of the course, so combining them gave us a representative of their post-knowledge. With this formula, we can therefore calculate the students' knowledge gains.

The means of each group's knowledge gain is visible in Table 5.5. From this table, we can conclude that the knowledge gain goes down the fewer interactions happen with the stars. The highest knowledge gain was in the top 25% of star interactions. The *super-learners* had the second highest average knowledge gain. Comparing all of the groups on their knowledge gain with one-way ANOVA yielded no significant results (F(7) = 0.634 & p = 0.728). A difference in knowledge gain is visible, but since there were no significantly different means between the groups we cannot accept H_2 .

	N	Mean	STD
Intersection of top 25%	17	0.16	1.39
Union of top 25%	76	0.14	1.17
Top 25% of stars	46	0.23	1.14
Middle (25% - 75%) of stars	55	-0.07	1.13
Bottom 25% of stars	52	-0.12	0.99
Top 25% of meaningful	47	0.07	1.27
Middle (25% - 75%) of meaningful	70	-0.06	1.03
Bottom 25% of meaningful	36	0.04	0.97

Table 5.5: The amount of students, the knowledge gain and its standard deviation for each group.

5.3. Post-Questionnaires and Qualitative Analysis

We invited five students for a Semi-Structured interview that was conducted by an invited expert not associated with this study. Three students appeared for the interview. At a later stage after the interview, we identified that the students belonged to the Moderate cluster. The interviews were recorded, transcribed by an external contributor, and anonymized before being made available for our analysis. Any identifiers are replaced with the students' *userid* in the system. The interviewer asked questions regarding all the different features of the dashboard and the student's opinions on them. All the students had varying opinions regarding the features, but some common elements were identified. This section goes over the interviews simultaneously and gives a summary of them.

Firstly, the students were asked about the learning material. While User 2002 did not use the learning material, the other two said that they used almost all of it to prepare for the final exam. User 2008 remarked about the usefulness of the different types of learning material: 'And with the extra learning materials, for example, the videos were all quite short and ... you just got a quick overview of how certain things work. With the articles you have the more detailed description of what actually happens with research into that field and makes you understand. ... It really helps you instead of: you just need to learn these six chapters for this exam.'. Even though not all of them used the learning materials as much, they all wanted the supplemental material to be included in other courses.

Secondly, the interviewer went over the progress bars for each concept in the course and explained the bars. Every student did not figure out completely how the learning progress was calculated and suggested, in future versions, to include an explanation near the progress bars. Furthermore, the students showed different opinions regarding the social comparison that could be done with the bars. User 2189 did not use the bars to compare themselves to not get pressured by it, while User User 2008 did not use the bars because they did not find it useful to compare. Even though 2002 did not use a lot of learning material, they did use the progress bars to compare their progress against others to see what concepts needed extra attention. In the end, all students wanted the progress bar to be included in other courses since they could see the helpful potential for other students.

Thirdly, the interviewer asked them about their opinions regarding the leaderboard. Similarly to the progress bars, the sorting of the leaderboard was not understood immediately. They had the same suggestion again, which was to include an explanation of the sorting and learning progress on the leaderboard. User 2002 did not use the leaderboard and even suggested that if it would be used in a future course to show it on a separate screen so it does not take up a lot of space on the main interface. User 2008 and User 2189 did use the leaderboard and both socially compared themselves against their peers. Both stated that because of this, they interacted more with the system to improve their score. User 2008 did remark that the current leaderboard was way too big and suggested that using relative scoring on the leaderboard could be more useful for the students.

Fourthly, the interviewer asked for suggestions on how to improve the dashboard. User 2002 noticed that two social comparison elements track the same thing, namely the progress bars and the leaderboard. They suggested making them track different elements: '... making the progress bar more about the practicals, the individual exercises, or the tests, instead of making them about the supplemental material.'. User 2002 and User 2008 both suggested including an automatic save in the practicums since that now needed to be done manually for each question, which caused them some issues. User 2189 suggested creating an opt-in feature for the progress bars and remarked: '... in the settings you could allow someone to put the comparative bar on, or leave it out to your own willing in that sense'.

Chapter 6

Discussion

Our research focused on finding the differences in interaction based on individual differences in students, like pre-knowledge and personality. Furthermore, we checked if low pre-knowledge students who improved had differences in interaction compared to students who did not improve. We found supporting evidence that personality did have an influence on the students' interactions on the dashboard. The four personality clusters showed different behaviors on the dashboard on the leaderboard. For the pre-knowledge aspect and low pre-knowledge students, we did not find supporting evidence. The complexities of most of the analysis were that they only used a small subset of students and this small subset was based on an arbitrary measure that we decided on. The dashboard also contained a bar that could be gamified, which we took into account with our smaller subset of students. Besides, we created personality clusters and explained them to the best of our ability. The Moderate cluster contained most learners with average subscale scores. During the interviews, even within the Moderate cluster learners showed different behavior on the different features of the dashboard.

In this section, we go deeper into these complexities and compare our results to previous work. Furthermore, we propose future work based on limitations and research gaps.

6.1. Comparing with previous work

As mentioned in a paper by A. Domínguez, et al [7], some students' behavior could be considered cheating the system, like quickly finishing exercises while not doing them to boost their scores. To counter these behaviors we analyzed and identified learners. However, classifying what can be called a meaningful interaction was difficult. For the learning material, we defined that a minute of observing the material would be sufficient enough. However, since learning materials vary in length, this classification possibly was not good enough for the different learning materials types. Meaningful interactions also could not be defined for other parts of the dashboard.

Concerning the low Cronbach's alpha for the Big 5 10-item personality inventory (TIPI), this feature is explained in the original design of the TIPI. TIPI was designed as a scale that concerns validity the most. Adapting the scale to also have high alpha values, would have a big cost in its validity. This directly counters the original goal of why TIPI was created [18].

6.2. Limitations and Future work

Due to time constraints and technical issues not all planned features were implemented into the interface. One of these features was tracking hovering actions on the dashboard. This would have been particularly useful since it would have allowed us to analyze interactions with the progress indicators. In the current implementation, there is nothing that tracks the interaction with them which made it impossible to analyze or reason about students' interaction with them. Another feature was tracking the scrolling actions on the leaderboard. This could have given us interesting insights into how the students used the leaderboards. For example, did the students only look at their placement (which did not require any scrolling) or did they look at other certain placements as well? Furthermore, as mentioned in the interview, students needed to manually save every question in practicums. This most likely led to some filled-in questions being counted as empty, which could have created wrong data for the practicums.

From the hierarchical clustering, the best explainable amount of clusters was 4. This conclusion was reached when observing the subscale scores and cluster sizes of different amounts of clusters. With fewer clusters, the group size differences became more prevalent. With both three and two clusters, there was always one very large group. With more clusters, the opposite problem was noticed. Other than clusters with very few students, there were also almost no differences in the added clusters. Furthermore, we wanted to have different groups with orientation and social comparison habits. We did not want to treat the six subscales as independent and unique categories, because we can multiple attributes from one subscale.

The dataset gathered from the tracking of a lot of interactions on the dashboard was very big and complex. There were a lot of different variables that could be analyzed and were analyzed. Due to page restraints, not a lot of analyzes that were done were included in this thesis. For example, a factor analysis was attempted on all the questions from the pre-questionnaire. There were also multiple analyzes done on week-by-week interaction data. Because of the page limits, this thesis could only include the analyzes that were mentioned in the results section.

Another analysis that was not included was the summary statistics of the post-questionnaire. Unfortunately, due to the low response rate, it was not included in this thesis.

6.2.1. Future work

During the design phase of the project, we thought of intriguing attributes that unfortunately were out of the scope for this project. An attribute to introduce for future work could be the use of guilds in the system. This would create another subset of groups, divided by for example their learning goals and patterns. Team based play also lessen the competitive burden on the individual [9] and hopefully allow for constructive competition. Next, since our dashboard included multiple social comparison elements, research if showing only one element would benefit a student more. The dashboard would then contain only one way of progress indication, like only a leaderboard or only the bars. Additionally, we propose some changes to the leaderboard. Previous work by Bai, et al [3], already showed us the implications of absolute or relative positions on a leaderboard. Introducing this to our dashboard could be interesting. Furthermore, limiting the students' visibility on the leaderboard could introduce some other behavior. For example, only showing the student a certain range around their placement. Would this change a student's perspective and opinion on the leaderboard? Research on leaderboards has been a popular topic in the gamification field. However, comparing the effectiveness of it concerning a student's traits and other elements of learning is still a new problem. Further research is required for this problem.

Chapter 7

Conclusion

This thesis aimed to portray the behavior of students on a dashboard containing both leaderboards and progress indicators. This was tested using a dashboard within *StudyLens* [1] during a Biology university course. The dashboard tracked the interactions of the students, which were used to analyze between different features of the students. Individual personality differences did show different behavior on the leaderboard. These differences could not be found when analyzing preknowledge differences among the learners. Even when taking the learners who performed a lot of self-reflection interactions and comparing them with learners who did less of those interactions, there was no significant difference found. With these findings, we conclude that more research is needed to answer whether these personality differences influence behavior on an online learning dashboard with multiple social comparison elements.

Chapter 8

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Appendix A

Evolution-2 schedule

Date	Lecture/Test available
06-02-2023	Formative test 1
06-02-2023	Lecture 1: Geografie van biodiversiteit and accompanying practicum
14-02-2023	Lecture 2: Variatie & mutatie and accompanying practicum
21-02-2023	Formative test 2
21-02-2023	Lecture 3: Patronen van Evolutie and accompanying practicum
28-02-2023	Lecture 4: Aardgeschiedenis & fossiele archief and accompanying practicum
14-03-2023	Lecture 5: Natuurlijke selectie and accompanying practicum
21-03-2023	Lecture 6: Interactie, coöperatie & conflict and accompanying practicum
28-03-2023	Formative test 3
28-03-2023	Lecture 7: Soorten & soortvorming and accompanying practicum

Table A.1: The schedule of Evolution-2. The answers of each practicum will also be made available two or three days after the practicum was available.

Appendix B

Results of the Ethics and Privacy Quick Scan

Response Summary:

Section 1. Research projects involving human participants

P1. Does your project involve human participants? This includes for example use of observation, (online) surveys, interviews, tests, focus groups, and workshops where human participants provide information or data to inform the research. If you are only using existing data sets or publicly available data (e.g. from Twitter, Reddit) without directly recruiting participants, please answer no. • Yes

Recruitment

P2. Does your project involve participants younger than 18 years of age? • No

P3. Does your project involve participants with learning or communication difficulties of a severity that may impact their ability to provide informed consent? • No

P4. Is your project likely to involve participants engaging in illegal activities? • No

P5. Does your project involve patients?

No

 P6. Does your project involve participants belonging to a vulnerable group, other than those listed above?
 Yes: Students

Ethics Warning. As you are dealing with vulnerable participants (yes to one (or more) of P2-P6) a fuller ethical review is required. Please add more detail on your participants here:

University of Utrecht Biology students following Evolution-2.

P7. Do you intend to be alone with a research participant or have to take sole responsibility for the participants at any point during your research activity?

• No

P8. Does your project involve participants with whom you have, or are likely to have, a working or professional relationship: for instance, staff or students of the university, professional colleagues, or clients?

No

Informed consent

PC1. Do you have set procedures that you will use for obtaining informed consent from all participants, including (where appropriate) parental consent for children or consent from legally authorized representatives? (See suggestions for information sheets and consent forms on <u>the website</u>.)

Yes

PC2. Will you tell participants that their participation is voluntary?
• Yes

PC3. Will you obtain explicit consent for participation?

Yes

PC4. Will you obtain explicit consent for any sensor readings, eye tracking, photos, audio, and/or video recordings?

Not applicable

PC5. Will you tell participants that they may withdraw from the research at any time and for any reason? • Yes

PC6. Will you give potential participants time to consider participation?
• Yes

PC7. Will you provide participants with an opportunity to ask questions about the research before consenting to take part (e.g. by providing your contact details)?

Yes

• 105

PC8. Does your project involve concealment or deliberate misleading of participants?
• No

Section 2. Data protection, handling, and storage

The General Data Protection Regulation imposes several obligations for the use of **personal data** (defined as any information relating to an identified or identifiable living person) or including the use of personal data in research.

D1. Are you gathering or using personal data (defined as any information relating to an identified or identifiable living person)?

No

Section 3. Research that may cause harm

Research may cause harm to participants, researchers, the university, or society. This includes when technology has dual-use, and you investigate an innocent use, but your results could be used by others in a harmful way. If you are unsure regarding possible harm to the university or society, please discuss your concerns with the Research Support Office.

H1. Does your project give rise to a realistic risk to the national security of any country? • No

H2. Does your project give rise to a realistic risk of aiding human rights abuses in any country? • No

H3. Does your project (and its data) give rise to a realistic risk of damaging the University's reputation? (E.g., bad press coverage, public protest.) • No

H4. Does your project (and in particular its data) give rise to an increased risk of attack (cyber- or otherwise) against the University? (E.g., from pressure groups.)

• No

H5. Is the data likely to contain material that is indecent, offensive, defamatory, threatening, discriminatory, or extremist?

No

- H6. Does your project give rise to a realistic risk of harm to the researchers?

 No
- H7. Is there a realistic risk of any participant experiencing physical or psychological harm or discomfort?
 No

H8. Is there a realistic risk of any participant experiencing a detriment to their interests as a result of participation?

No

H9. Is there a realistic risk of other types of negative externalities?
• No

Section 4. Conflicts of interest

C1. Is there any potential conflict of interest (e.g. between research funder and researchers or participants and researchers) that may potentially affect the research outcome or the dissemination of research findings?

No

C2. Is there a direct hierarchical relationship between researchers and participants?

No

Section 5. Your information.

This last section collects data about you and your project so that we can register that you completed the Ethics and Privacy Quick Scan, sent you (and your supervisor/course coordinator) a summary of what you filled out, and follow up where a fuller ethics review and/or privacy assessment is needed. For details of our legal basis for using personal data and the rights you have over your data please see the <u>University's privacy information</u>. Please see the guidance on the <u>ICS Ethics and Privacy website</u> on what happens on submission.

Z0. Which is your main department?

Information and Computing Science

Z1. Your full name:

P.S.L. Alvarez

Z2. Your email address:

p.s.l.alvarez@students.uu.nl

Z3. In what context will you conduct this research?

- As a student for my master thesis, supervised by:: S.A. Sosnovsky
- Z5. Master programme for which you are doing the thesis
 - Game and Media Technology
- Z6. Email of the course coordinator or supervisor (so that we can inform them that you filled this out and provide them with a summary):

s.a.sosnovsky@uu.nl

Z7. Email of the moderator (as provided by the coordinator of your thesis project): a.volk@uu.nl

- **Z8. Title of the research project/study for which you filled out this Quick Scan:** Comparing a leaderboard with topic-based indicators against topic-based indicators alone on social comparison habits, engagement and performance
- **Z9. Summary of what you intend to investigate and how you will investigate this (200 words max):** Investigate the students' preferences, engagement and performance of the dashboard in StudyLens. To investigate this, we track the interactions with the dashboard, perform interviews and questionnaires.

Z10. In case you encountered warnings in the survey, does supervisor already have ethical approval for a research line that fully covers your project?
• Yes

Z11. Provide details on the ethical approval (e.g. ethical approval number) The ERB application number is "Bèta S-23910"

Scoring

- Privacy: 0
- Ethics: 1

Appendix C

Information and Consent form

Information and Consent Form (StudyLens Evo-2)

Learning analytics in Biology courses

Contact: Dr. Sergey Sosnovsky Software Technology for Learning and Teaching Department of Information and Computing Science Utrecht University Email: s.a.sosnovsky@uu.nl

Date: 01/09/23

Wat is het doel van deze studie? What is the purpose of this study?

In this course, you have access to the learning analytics platform StudyLens. This study investigate how you use it, benefit from it and how the platform can be further improved.

Wat moet ik doen als ik aan het onderzoek deelneem?

What do I do if I participate in the study?

You attend the course as usual. Through the StudyLens platform, you will get access to self-assessment quizzes and remedial learning material. After each quiz, StudyLens will display your progress and will navigate you to the learning material that should help you resolve your learning difficulties. You are also asked to fill-in one questionnaire in the beginning of the course and one more at the end of the course.

Hoe lang ben ik met het onderzoek bezig?

How long will I be doing the research?

The data collection phase runs for the duration of the course.

Wat zijn de mogelijke risico's of ongemakken?

What are the possible risks or inconveniences?

There are no risks associated with using the system. The learning material for the system are designed with

the help of your course instructors, hence you can be sure in their quality. The experimenters do not have access to your identity, only to the login you have been provided with, hence there is no way to associate your data with who you are. Your course instructors will have access to your quiz scores. All other data you produce will be available only to the experimenters and only in the anonymized form.

Zijn er mogelijke voordelen?

Are There Possible Benefits? (Rewards? Souvenir?)

There are no additional rewards except for the opportunity to learn your course material in a more interactive manner.

Zullen mijn persoonsgegevens en de informatie over mijn deelname vertrouwelijk behandeld worden?

Will my personal data and information about my participation be treated confidentially? All the data you generate while using the system and answering questionnaires is anonymised and stored

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securely on UU servers. If a research paper is written about this experiment, no information in such a paper

can be used to personally identify you.

Wat zijn mijn rechten als ik aan het onderzoek deelneem? What are my rights if I participate in the study?

According to GDPR, you have the following rights:

- The Right to Information
- The Right of Access
- The Right to Rectification
- The Right to Erasure
- The Right to Data Portability
- The Right to Object
- The Right to Avoid Automated Decision-Making

The informed consent form (below) explains these rights in more details

Met wie kan ik contact opnemen als ik vragen over het onderzoek heb? Who can I contact if I have questions about the study?

If you have any questions, comments, or concerns regarding this research project, please contact Dr. Sergey Sosnovsky (s.a.sosnovsky@uu.nl).

If you have any questions about your rights as a participant in the research or if you have any concerns or complaints about the way in which the participants in the research are treated, you can send an email to the privacy officer of Utrecht University: <u>privacy@uu.nl</u>

Informed consent

Software technology for learning and teaching in university courses

Contact: Dr. Sergey Sosnovsky Software Technology for Learning and Teaching Department of Information and Computing Science Utrecht University Email: s.a.sosnovsky@uu.nl

Date: 01/02/23

I have read and understood the information for the participant (Right to Information). I had enough time and information to decide whether to participate. If I have questions, I know whom to contact.

I know that participation in this experiment is completely voluntary. I am aware that I can decide at any time to stop participating (Right to Object) and have my data erased (Right to Erasure). I do not have to give a reason for that.

I know that the researchers conducting this experiment can see my data in anonymized form. The names and contact details of these people are known to me. I have the right to view the way in which my data is stored and processed (Right to Access). If the data is erroneous or incomplete, I am entitled to have it corrected (Right to Rectification). I can also request to get access to it for my own purpose (Right to Data Portability).

At no point, I am at risk of potentially damaging decisions due to automated decision making and profiling based on my data (Right to Avoid Automated Decision-Making).

I give permission to use my data for the purposes stated in the information letter.

I give my permission to keep the data for another 10 years after the end of this study for further analysis in the context of this study (if necessary).

I hereby declare that I have sufficiently informed this participant about this study.

If information becomes known during the study that could influence the consent of the participant, I will inform him / her in a timely manner in a way that ensures that the information has reached the participant.

Name of researcher: Sergey Sosnovsky

1. StudyLens Login

Please add the username starting with evo2___.

2.	Do	vou	agree	to	partici	pate	in	this	stud	v?
۷.	20	you	agree	ιυ	partici	pare		tins	stuu	y:

O Yes

O No

3. Would you be willing to participate in a short interview about your experience with StudyLens? Such an interview would take place after the midterm.

) Yes	
) No	
4.	ate	
		•

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Appendix D

Pre-questionnaire

24/04/2023, 16:38

Questionnaire for Evo2 Students

Questionnaire for Evo2 Students

This form will take 10-15 minutes to fill and will give additional information to the developers to improve the interface to suit the needs of individual students.

* Required

1. StudyLens Username * Please enter the username you login with on StudyLens. It usually starts with evo2____.

2. Would you be interested in participating a future study (interview etc.) related to this?

O Yes

O No

Questionnaire for Evo2 Students

We'll ask a few questions about your style of learning.

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Questionnaire for Evo2 Students

 The statements below are related to how you think and feel about your learning experiences and your goals. Select one of the options based on the prompt on the left.

	Not at All True (1)	(2)	(3)	(4)	(5)	(6)	Very True (7)
It is important for me to do better than other students	0	0	0	0	0	0	0
It is important for me to do well compared to others in this class	0	0	0	0	0	0	0
My goal in this class is to get a better grade than most of the other students	0	0	0	0	0	0	0
I worry that I may not learn all that I possibly could in this class	0	0	0	0	0	0	0
Sometimes I'm afraid that I may not understand the content of this class as thoroughly as I'd like	0	0	0	0	0	0	0
I am often concerned that I may not learn all that there is to learn in this class	0	0	0	0	0	0	0
l want to learn as much as possible from this class.	0	0	0	\bigcirc	0	\bigcirc	0
It is important for me to understand the content of this course as thoroughly as possible	0	0	0	0	0	0	0
l desire to completely master the material presented in this class	0	0	0	0	0	0	0
l just want to avoid doing poorly in this class	0	0	0	0	0	0	0
My goal in this class is to avoid performing poorly	0	0	\bigcirc	\bigcirc	\bigcirc	0	0
My fear of performing poorly in this class is often what motivates me.	0	0	0	0	0	0	0

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Questionnaire for Evo2 Students

4. Think about past situations and select one of the options for each prompt on the left.

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
l always pay a lot of attention to how I do things compared with how others do things.	0	0	0	0	0
l often compare how l am doing socially (e.g., social skills, popularity) with other people.	0	0	0	0	0
l am not the type of person who compares often with others.	0	0	0	0	0
I often try to find out what others think who face similar problems as I face.	0	0	0	0	0
l always like to know what others in a similar situation would do.	0	0	0	0	0
If I want to learn more about something, I try to find out what others think about it.	0	0	0	0	0

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Questionnaire for Evo2 Students

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
l see myself as someone who is reserved	0	0	0	0	\bigcirc
l see myself as someone who is generally trusting	0	\bigcirc	\bigcirc	\bigcirc	0
I see myself as someone who tends to be lazy	0	0	0	0	\bigcirc
l see myself as someone who is relaxed, handle stress well	0	0	0	0	0
I see myself as someone who has very few artistic interests	0	\bigcirc	\bigcirc	\bigcirc	0
l see myself as someone who is outgoing and sociable	0	0	0	0	0
I see myself as someone who tends to find fault with others	0	0	0	0	0
l see myself as someone who does a thorough job	0	0	0	0	0
l see myself as someone who gets nervous easily	0	\bigcirc	0	0	0
l see myself as someone who is has an active imagination	0	0	0	\bigcirc	0

5. These questions discuss your lifestyle in general. Select one of the options based on the prompt on the left.

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Appendix E

Post-questionnaire

Evo2 - Studylens Post Course Questions

In this course, you have had access to a learning tool StudyLens, where you could take Quizzes, work on the Practicums, monitor your progress, and access additional Learning Material (like factsheets and instructional videos). This short questionnaire helps us understand your experience with StudyLens and improve its functionality.

The survey will take approximately 5 minutes to complete.

* Required

Part A - General

What was your Studylens Username? Studylens usernames look like evo2999. *

How was your experience with Studylens? For each of the statements below, select one of the five options. *

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
l enjoyed working with StudyLens	\bigcirc	\bigcirc	\bigcirc	\bigcirc	0
I found StudyLens useful in this course	0	0	\bigcirc	0	0
Using StudyLens helped me prepare for the exams	0	\bigcirc	\bigcirc	0	0
I think StudyLens was effective in guiding me towards the learning materials that I should read/view	0	0	0	0	0
I think that the interface of StudyLens was easy to use	0	0	\bigcirc	0	0
The additional learning material was helpful	0	0	0	0	0

Part B1 - Progress Indicators

Within StudyLens you could test your knowledge and track your progress on different topics with progress indicators (see the attached image).

Look at the statements on the left and select one of the options for each statement. The options range from Strongly Disagree to Strongly Agree \ast



	Strongly Disagree	Disagree	Neutral	Disagree	Agree	Strongly Agree
I looked at the progress indicators frequently.	\bigcirc	\bigcirc	\bigcirc	\bigcirc	\bigcirc	0
The progress indicators motivated me to study more	\bigcirc	0	\bigcirc	0	0	0
The progress indicators guided me towards what to learn next.	\bigcirc	0	\bigcirc	0	0	0
l would have used StudyLens just as much as l would have without the progress indicators.	0	0	0	0	0	0
l frequently compared my scores with the social scores (class average bar).	0	0	0	0	0	0
I found it helpful to see how do I compare with respect to the class average	0	0	0	0	0	0
I felt better when I compared myself with the class average	0	0	0	0	0	0
l felt l should study more when l looked at the class average	\bigcirc	0	\bigcirc	\bigcirc	0	\bigcirc

?

Part B2 - Leaderboard

A large part of the StudyLens Dashboard is a Leaderboard where you can see where you stand in the whole class based on the Assessment Tests you gave in the platform and track your Learning Progress. There was also an option to filter the leaderboard based on different competencies related to this course.

Look at the statements on the left and select one of the options for each statement. The options range from Strongly Disagree to Strongly Agree \ast

Total	Fitness Natuurlijke se	electie Speciatie	Variatie Genetische drift	Fylogenie 📀
	NAME	SCORE	LEARNING	PROGRESS
1. 🧶	evo2203	10.00	409%	
2. 😒	evo2089	9.38	47.95%	
3. 😸	evo2049	9.38	20.47%	
4. 🤒	evo2042	8.75	84.219	6
5. 🥩	evo2153	8.75	43.27%	
6. 🥶	evo2125	8.75	40.35%	
7. 🎯	evo2171	8.75	21.64%	
8. 🤹	evo2022	8.75	8.77%	
9. 过	evo2013	8.44	42.69%	
10. 🍅	evo2119	8.44	22.22%	

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
l looked at the Leaderboard frequently	\bigcirc	0	0	0	0
The Leaderboard motivated me to study more	0	0	0	0	0
The Leaderboard' s progress indicator guided me towards what to learn next.	0	0	0	0	0
I would have used StudyLens just as much as I would have without the Leaderboard.	0	0	0	0	0
I frequently checked my position on the Leaderboard	0	0	0	0	0
l frequently checked my learning progress on the Leaderboard	0	0	0	0	0
I felt better when I looked at my position on the Leaderboard	0	0	0	0	0
l found it helpful to see where I stand on the leaderboard	\bigcirc	0	\bigcirc	0	0
I felt like I should study more when I looked at my position on the Leaderboard	\bigcirc	0	0	0	0

Is there something else you would like to tell us about your experience with the Leaderboard?

Part C - Overall Experience and Feedback

8

StudyLens interface was a combination of Leaderboard and Progress Indicators.

Look at the statements on the left and select one of the options for each statement. The options range from Strongly Disagree to Strongly Agree \ast

	Strongly Disagree	Disagree	Neutral	Agree	Strongly agree
I feel that the interface helped me decide what I wanted to do next	0	0	0	0	0
I feel that StudyLens motivated me to study more	0	0	0	0	0
l feel that the system helped me understand the level of my knowledge	0	0	0	0	0
l paid attention to how I was performing with respect to my classmates	0	0	0	0	0
I liked to know how others were performing in the course	0	0	\bigcirc	0	0

9

What part of the Dashboard you interacted with more? *

O Leaderboard

O Progress Indicators

O Both

10

What part of the Dashboard was more helpful in motivating you to study? *

O Leaderboard

O Progress Indicators

O Both

11		
Would y	ou like to elaborate on your answers to the past two questions?	
10		
12		
12 What el	e would you like to tell us about how Studylens helped you or could have helped you	
¹² What el better?	e would you like to tell us about how Studylens helped you or could have helped you feel free to write anything.	
12 What el better?	e would you like to tell us about how Studylens helped you or could have helped you eel free to write anything.	
12 What el better?	e would you like to tell us about how Studylens helped you or could have helped you Feel free to write anything.	
12 What el better?	e would you like to tell us about how Studylens helped you or could have helped you Feel free to write anything.	
12 What el better?	e would you like to tell us about how Studylens helped you or could have helped you eel free to write anything.	
12 What el better?	e would you like to tell us about how Studylens helped you or could have helped you eel free to write anything.	
12 What el better?	e would you like to tell us about how Studylens helped you or could have helped you Feel free to write anything.	